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I. INTRODUCTION

A. Nature of the Problem

In agricultural and nonagricultural business fields, surveys are used to determine from businessmen their expectations and plans. On the basis of information from the surveys, phenomena of the real world can be forecast. Forecasting by those surveys can take two forms, direct or indirect. The direct method secures information on peoples' attitude and plans with regard to the items of interest, for example, plans to produce. Forecasts are then made directly from the collected surveys. For example, a group of farmers might be asked the number of acres on which they plan to grow corn in the coming spring. Then, planting intentions of the sample could be used to forecast total planting acreages for all farmers, and the production of corn will be forecast. With the indirect approach, the researchers use the survey method to predict variables closely related to the items covered in the study. Forecasts are generated by means of previously derived relationships between the survey variables and the items of interest.

In 1961, Modigliani and Cohen (20) discussed the use of plan or attitude data in forecasting and in economic analysis. The concepts of anticipation function, decision function and realization function were introduced. The anticipation function deals with a firm's anticipations and initial conditions. The decision function relates decisions on a firm's anticipated future behavior to initial conditions. The realization function accounts for divergence between decisions and actions and for variables that may cause actual behavior to differ from planned behavior. Modigliani and Cohen showed how anticipations affect decisions, and how actions are affected by decisions and by divergences between realizations and anticipations.

Several studies have been done in the area of nonagricultural business fields. In the January and February surveys by the Commerce-Securities and Exchange Commission, businessmen were questioned concerning their anticipated sales for the year. Okun (22) found that results of the surveys have no predictive value. Annual sales were more accurately predicted by extrapolating the seasonally adjusted January level of sales. However, the deviations of actual sales from anticipated sales explained much of the variance in deviations of actual from intended investment. The final finding is an example of the realization function. Okun concluded that it seems safe to predict that economists would continue to confront businessmen with questions about their intentions and that the subjective data would be valuable in forecasting economic activities and in understanding business decision-making.

Orr (23) found that the sales expectation variable was positively and significantly related to inventory investment. Thus, this variable could be used to predict actual inventory investment.

Pashigian (25) also studied the forecasting value of the Commerce-Securities and Exchange Commission data on sales anticipations and concluded that these data were not likely to be useful for forecasting actual sales.

In a macro-economic model, Adams and Duggal (1) studied the comparison of the Wharton Mark III macro-model with anticipatory data and the standard model of Wharton Mark III (model without anticipatory data). They concluded that anticipatory variables can make a valuable contribution to model accuracy. In addition, they found that incorporating anticipations variables tended to reduce error even in the case where no advance information was introduced. From turning point analysis, the forecasting anticipatory version simulates more turning points, as true turning points, than does the standard version.

Although many studies have been done in the area of business, there have been only a few in the agricultural sector. In a study of farm turkey prices and production, when Ladd (18) restricted himself to nonanticipatory data, he could find no better way to predict turkey slaughter for the following year than to use lagged market price and time trend. Adding information on farmer's January 1 intentions to raise turkey to an equation containing these two objective variables, resulted in all coefficients being highly significant. The revised equation indicated better predicted values of variation in turkey slaughter than the values obtained from the equation using objective data alone. The result did provide grounds for believing that estimates of supply response of farm products could be improved by relating planted acreages to intended acreages and to objective variables that account for differences between intentions and realizations.

B. Objective

The main objective of this study is to determine efficient methods for using data on farmer's intentions in estimating farm supply response.

The intention variables to be covered in this study are March 1 intentions to plant corn, soybeans, oats, barley, sorghum and wheat.

The second objective is to compare the accuracy of estimates from the basic models without subjective variables with revised models with subjective variables.

C. Procedure

Many econometric models of agricultural sectors have been published. This study will be built upon these models. Variations of these models will be developed by incorporating subjective data on farmers' plans or intentions. The models will assume maximal expected profit of the firm.

The variables on intentions will be treated as additional independent variables in the farm-supply equation to test the hypothesis: a better explanation of planted acreage can be obtained from a combination of subjective data and objective data than can be obtained from the use of either type of data by itself.

The main effort here is to determine whether information on farmers' intentions can be used to estimate commodity supply response. The investigation on inter-commodity relations is to determine what relation may exist between planted acreage and intended acreages for other grains.

II. ECONOMIC MODEL: THEORETICAL CONSIDERATION

A. Mathematical Model and Classical Theory of the Firm

Classical theory assumes that the farm firm possesses the objective of profit maximization. Profit is the difference between total revenue and total cost of the firm. A firm transforms the inputs of land, labor and capital into product outputs, subject to the technical constraints of the production functions.

Consider a farm firm producing n outputs $(q_1,\ldots,q_n)$ using m-n inputs $(x_{n+1},\ldots,x_m)$. Let the production relationship between the quantity of inputs employed and the outputs produced be stated in implicit form as

$$f(q_1,q_2,\ldots,q_n,x_{n+1},x_{n+2},\ldots,x_m) = 0 \qquad (2.1)$$

where (2.1) is assumed to possess continuous first- and second-order derivatives. It is also assumed that (2.1) is written in such a way that its partial derivatives for outputs are normally positive and its partial derivatives for inputs are normally negative, that is:

$$f_{q_i} > 0, \quad f_{x_j} < 0.$$

The total cost of producing a selected combination of outputs is defined as

$$TC = w_{n+1}x_{n+1} + w_{n+2}x_{n+2} + \ldots + w_m x_m \qquad (2.2)$$

or, in matrix notation form,

$$TC = \Omega' X$$

where

TC is the total cost,

Ω is the vector of prices of inputs,

X is the vector of quantities of inputs; and

the price of the j^{th} input x_j is given as w_j, $j = n+1, n+2, \ldots, m$.

The total revenue obtained from a selected output combination is defined as

$$TR = P_1 q_1 + P_2 q_2 + \ldots + P_n q_n \qquad (2.3)$$

where TR is the total revenue, the price of the i^{th} product q_i is given as P_i, $i = 1, 2, \ldots, n$.

The problem facing the firm then is to find the optimum combination of inputs and outputs that will maximize profit. Profit is defined here as the difference between the total revenue from the sale of all outputs and the total cost of all inputs. The decision criterion for the firm then becomes the maximization of

$$\pi = TR - TC$$

$$= \sum_{i=1}^{n} P_i q_i - \sum_{j=n+1}^{m} w_j x_j \qquad (2.4)$$

subject to the Equation (2.1).

1. First-order condition of profit maximization

The profit maximization solution can be determined by the use of a Lagrangian technique and by maximizing (2.5)

$$L = \pi-\lambda f(q_1,q_2,\ldots,q_n, x_{n+1},\ldots,x_m) \tag{2.5}$$

with respect to the m variables.

The first-order or necessary conditions for profit maximization are determined by setting the first partial derivatives of (2.5) equal to zero. This will give us the results as follows:

$$\partial L/\partial q_i = P_i-\lambda f_i = 0, \quad i = 1,2,\ldots,n \tag{2.6}$$

$$\partial L/\partial x_j = -w_j-\lambda f_j = 0, \quad j = n+1,\ldots,m \tag{2.7}$$

$$\partial L/\partial \lambda = f(q_1,\ldots,q_n, x_{n+1},\ldots,x_m) = 0 \tag{2.8}$$

where f_i or f_j is the partial derivative of (2.1) with respect to its corresponding i^{th} product or j^{th} input argument. The interpretation of those conditions is derived as follows:

1) From set of Equations (2.6), pick any pair, say i^{th} and k^{th} of the n relations. Moving the second terms across the equal sign and dividing one by the other yields

$$P_i/P_k = f_i/f_k \qquad i,k = 1,\ldots,n \quad i \neq k \tag{2.9}$$

Thus, for profit maximization, the marginal rate of transformation between any two products must be equal to their respective price ratios. This is the so-called product-product relationship in a profit maximizing competitive firm.

2) From set of Equation (2.7), consider any pair, say j^{th} and k^{th} of the m-n relations. When they are treated similarly to the relations in (2.6), then

$$w_j/w_k = f_j/f_k \tag{2.10}$$

$$j,k = n+1,\ldots,m \quad j \neq k;$$

the marginal rate of substitution of x_j for x_k (ratio of marginal physical products) must equal the price ratio in the market. This is the input-intput relationship.

3) From the set of Equations (2.6) and (2.7), consider q_i and x_j, then

$$w_j/P_i = f_j/f_i, \quad i \neq j, \quad i = 1,\ldots,n \quad j = n+1,\ldots,m \tag{2.11}$$

Thus, the third decision rule is: the marginal physical product of input x_j in production of output q_i is equal to the real factor cost of x_j. This is the product-input relationship.

Equation (2.8) fulfills the constraints of being on the boundary of the production surface; it guarantees that the solution is feasible.

This theoretical presentation can be found in most micro-theory text books, especially Henderson and Quant (9, pp. 67-69).

In conclusion, production theory indicates that for profit maximization the marginal rate of transformation of all products and the marginal rate of substitution for all inputs should be equal to their respective price ratios. In addition, when considering relations between inputs and products, resource inputs should be used up to the point that the values of their marginal products are equal to their prices or so that the marginal physical product for any input is equal to the input-product price ratio.

2. <u>Second-order condition</u> (9, pp. 96-97)

The second-order conditions, which must hold for the solution set to be the set of profit maximization, require that the principal minors of the determinant of the bordered Hessian matrix alternate in sign, i.e.,

$$\begin{vmatrix} \lambda f_{11} & \lambda f_{12} & f_1 \\ \lambda f_{21} & \lambda f_{22} & f_2 \\ f_1 & f_2 & 0 \end{vmatrix} > 0, \ldots,$$

$$(-1)^m \begin{vmatrix} \lambda f_{11} & \cdot & \cdot & \cdot & \lambda f_{1m} & f_1 \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \lambda f_{m1} & & & & \lambda f_{mm} & f_m \\ f_1 & \cdot & \cdot & \cdot & f_m & 0 \end{vmatrix} > 0$$

where

$$f_{ij} = \partial^2\pi/\partial x_i \partial x_j \quad \text{or} \quad \partial^2\pi/\partial x_i \partial q_j \quad \text{or}$$

$$\partial^2\pi/\partial q_i \partial x_j \quad \text{or} \quad \partial^2\pi/\partial q_i \partial q_j,$$

and

$$f_i = \partial f/\partial x_i \quad \text{or} \quad \partial f/\partial q_i;$$

$$i,j = 1,\ldots,n,n+1,\ldots,m.$$

3. Derivation of product supply and input demand functions

In deriving product supply and input demand functions, the comparative statics analysis could be used. If one or more prices change, the profit maximization firm will adjust inputs and outputs so as to maintain the maximum profit. Let us differentiate Equations (2.6), (2.7) and (2.8) totally letting $q_i,\ldots,q_n$, $x_j,\ldots,x_m$, $P_i,\ldots,P_n$, $w_j,\ldots,w_m$ and λ change.

$$
\begin{aligned}
&\lambda f_{11}dq_1+\lambda f_{12}dq_2 +\ldots+ \lambda f_{1,n+1}dx_1 +\ldots+ \lambda f_{1,m}\, dx_m+f_1 d\lambda = dP_1\\
&\lambda f_{21}dq_1+\lambda f_{22}dq_2 +\ldots+ \lambda f_{2,n+1}dx_1 +\ldots+ \lambda f_{2,m}\, dx_m+f_2 d\lambda = dP_2\\
&\quad\vdots \qquad\qquad \vdots \qquad\qquad\qquad \vdots \qquad\qquad\qquad\quad \vdots \qquad\quad \vdots \qquad \vdots\\
&\lambda f_{m,1}dq_1+\lambda f_{m,2}dq_2+\ldots+ \lambda f_{m,n+1}dx_1 +\ldots+ \lambda f_{m,m}dx_m+f_m d\lambda = dw_m\\
&f_1 dq_1 + f_2 dq_2 +\ldots+ f_{n+1}dx_1 +\ldots+ f_m dx_m+0\, d\lambda = 0
\end{aligned}
\tag{2.12}
$$

Multiplying the first m equations by $1/\lambda$ and writing in matrix form, we have:

$$
\begin{bmatrix}
f_{11} & f_{12} & \cdots & f_{1m} & f_1\\
f_{21} & f_{22} & \cdots & f_{2m} & f_2\\
\vdots & \vdots & & \vdots & \vdots\\
f_{m1} & f_{m2} & \cdots & f_{mm} & f_m\\
f_1 & f_2 & \cdots & f_m & 0
\end{bmatrix}
\begin{bmatrix}
dq_1\\ dq_2\\ \vdots\\ dx_m\\ 1/\lambda\ d\lambda
\end{bmatrix}
=
\begin{bmatrix}
-1/\lambda\ dP_1\\ -1/\lambda\ dP_2\\ \vdots\\ -1/\lambda\ dw_m\\ 0
\end{bmatrix}
\tag{2.13}
$$

or, in short from:

$$FQ = P \tag{2.14}$$

We can obtain the solution for Q as follows:

$$Q = F^{-1}\ P \tag{2.15}$$

The meaning of the above solution is that the derived demand for inputs and the supply of products depend on the vector of prices of all inputs and products of the firm involved.

From the qualitative analysis, Huffman (13) concluded that, other things being constant, the rise in one price (output or input) may, in general, cause the quantity of output supplied or input demanded to change in any direction or to not change at all. However, for final products, the quantity supplied of q_i increases as its own price increases (other things being constant), i.e., the supply curve has a positive slope. For any inputs, the quantity demanded of x_i decreases when its own price increases. From this derivation, we will have the demand for inputs and supply of outputs functions. They depend on the prices of all inputs and outputs included in the model.

B. Maximizing Expected Profit of the Farm Firm

The marginal conditions presented above must hold *ex post* if profits for an agricultural firm are to be maximized. With perfect knowledge, a farm firm decision-maker could develop a plan that would utilize the decision rules and satisfy those conditions. However, in the real world, farmers don't know the prices of products they will sell in the future when they make the decisions. Those profit maximizing conditions then are not likely to be met except by chance.

It may be assumed that the farm firm doesn't know the exact prices of products in the growing season, but knows the cost of inputs because the prices of fertilizers and chemical products are set by the industrial sector and are rather fixed through time during one season. It is reasonable to assume fixed input prices for the farmer producing annual crops. Now, the farm firm's decision-making will depend on expected product prices under the assumption of maximization of expected profit.

The model of Hazell and Scandizzo (8) modified by the author of this thesis, will be presented here:

Define $\hat{p}$ = an nxl vector of expected product prices,

c = nxl vector of unit costs,

x = an nxl vector of enterprise levels, i.e., acreages planned to produce product i,

M = an nxn diagonal matrix of enterprise yields with j^{th} diagonal entry m_j,

and

$q = Mx$ is the nxl vector of total products.

Then, the objective function for an individual farm problem is

$$\text{Max. } E(\pi) = \hat{p}'q - c'x \tag{2.16}$$

and this is to be maximized over some set of technology constraints which are usually specified to be linear.

Let the linear technology constraints for the farm be denoted by

$$Dx \leq b \tag{2.17}$$

the Lagrangian function for maximizing (2.16) over this set is:

$$L = \hat{p}'Mx - c'x + v'(b-Dx) \tag{2.18}$$

where v is a vector of Lagrangian multipliers.

An optimal solution to the problem is then a saddle point. To maximize (2.16) subject to (2.17), the Kuhn-Tucker conditions are used. The first-order or necessary conditions are

$$\partial L/\partial x \leq 0, \quad \partial L/\partial v \geq 0 \tag{2.19}$$

$$x\partial L/\partial x = 0, \quad v\partial L/\partial x = 0 \tag{2.20}$$

$$x \geq 0, \quad v \geq 0$$

Of these, the requirements in (2.20) are the complementary requirements that an activity cannot be active and at the same time have a nonzero opportunity cost and that a resource cannot be slack and at the same time have a nonzero multiplier value.

Applying the first-order condition in (2.19) to (2.18) gives

$$\partial L/\partial x = \hat{p}'M - c' - v'D \leq 0 \tag{2.21}$$

$$\partial L/\partial v = b - Dx \geq 0 \tag{2.22}$$

(2.22) is the feasibility requirement.

Taking the j^{th} element of the vector $\partial L/\partial x$, rearranging terms, and dividing by m_j,

$$\hat{p}_j \leq 1/m_j [\sum_k v_k d_{kj} + c_j] \tag{2.23}$$

This states that for each product the marginal cost per unit of product must be equal to or greater than the expected price of that product. The marginal cost is comprised of the own-product marginal cost c_j/m_j plus the opportunity costs $1/m_j \sum_k v_k d_{kj}$ as reflected in the shadow prices of the resources used by that activity.

While (2.23) is a necessary condition, it is clear from duality theory that the condition will always be satisfied as an equality in an optimal solution for all activities which enter the basis. Consequently, the price-equals-marginal cost rules can be written as:

$$\hat{p}_j = 1/m_j [\sum_k v_k d_{kj} + c_j] \quad \text{for} \quad x_j > 0 \tag{2.24}$$

The right hand side of (2.24) is then the supply function for the farm as implicitly embedded in the mathematical programming model. This is a basic behavioral relationship and expresses the farmer's determination of x_j given his expectation about yields and prices. That is,

$$x_j = f_j(M,\hat{p}) \tag{2.25}$$

everything else being constant.

Multiplying by the mean yield m_j, a conditionally expected supply function is immediately obtained:

$$E(q_j|x_j) = m_j x_j = m_j f_j(M,\hat{p}) \tag{2.26}$$

Since all the expectations involved are subjective anticipation, it is useful to denote (2.26) as the anticipated supply functions.

By summing, the aggregate decision and anticipated supply function can be obtained. Ignoring aggregation problems, the j^{th} decision function can be written as

$$X_j = f(W,\hat{P}) \tag{2.27}$$

and the j^{th} supply function can be written as

$$E(Q_j|X_j) = w_j X_j = w_j f(W,\hat{P}) \tag{2.28}$$

where X_j, Q_i, W, $\hat{P}$ are suitable aggregates of x_j, q_j, M, $\hat{p}$ respectively, and w_j is the j^{th} diagonal element of W.

C. A Meaningful Model with Government Policy Implementation

The model in Section II.B could be called a free market model. Decisions which are derived depend on expected prices and yields. For the U.S. agricultural economy, analysis of agricultural acreage response is difficult because of the establishment and frequent revision of the government farm commodity programs. Just (16) has developed an acreage response model for empirical studies in which he considers subsidies, price supports, acreage allotments, and diversion programs. He presented the free-market model first, then the possible effects of taxes, subsidies, and price supports were discussed, and finally the effects of allotments and diversion requirements were considered. For the free market model, decisions depend on expected prices and yields as the result from the previous model shows. In empirical analysis, Just used as one variable the product of expected price and expected yield to get the return on one acre of land used in planting the particular crop. In formulating the expected prices and yields, he used the geometric lag distribution, which will be considered in the next part of this chapter.

Suppose S_t is a vector of economic state variables including prices and yields of the crops for period t and that decision-makers form subjective distributions for those stated variables in period t-1. If only the subjective means change and all higher subjective moments (variance, etc.) are considered constant, then subjective knowledge is generally described by an expectation (or means) vector,

$$m_t = \sum_{k=0}^{\infty} a_k S_{t-k-1} \tag{2.29}$$

where

a = weights of distributed lag.

Then the farmer's acreage decision depends on the expectation vector as follows:

$$x_t = f(m_t) \tag{2.30}$$

For policy implementation, the model of (2.30) could be modified and extended as described in detail in Just (16). The modifications of a decision that might result from government intervention were considered. The government was assumed to intervene in any combination of the following ways:

1) By provision of subsidies or imposition of taxes on inputs and outputs;

2) By imposition of restrictions on the use of certain inputs (i.e. land);

3) By establishment of price support levels; and

4) By the voluntary program.

The most general of Just's models might be expressed as a linear model as follows: (16, pp. 448-449)

$$A_{tj} = \alpha_{0j}+\beta_{1j}[\sum_{k=t-t_0}^{\infty} \theta(1-\theta)^{k-t+t_0}(S_{t-k-1}+S^{**}_{t-k-1})](1-\theta)^{t-t_0}$$

$$+ \beta_{1j}[S^{*}_{t} + \sum_{k=0}^{t-t_0-1} \theta(1-\theta)^{k}(S_{t-k-1}+S^{**}_{t-k-1})]$$

$$+ \beta_{2j}I^{*}_{t} + \beta_{3j}d^{**}_{t} + \beta_{4j}\psi^{*}_{t} + \beta_{5j}d^{+}_{tj} + \varepsilon_{tj} \qquad (2.31)$$

Since

$$\sum_{k=t-t_0}^{\infty} \theta(1-\theta)^{k-t+t_0}(S_{t-k-1}+S^{**}_{t-k-1})$$

is unobservable, it can be treated as a parameter to be estimated so the model becomes

$$A_{tj} = \alpha_{0j} + \beta^{*}_{1j}(1-\theta)^{t-t_0} + \beta_{1j}m^{**}_{t}$$

$$+ \beta_{2j}I^{*}_{t} + \beta_{3j}d^{**}_{t} + \beta_{4j}\psi^{*}_{t}$$

$$+ \beta_{5j}d^{+}_{tj} + \varepsilon_{tj} \qquad (2.32)$$

where

$$\beta^{*}_{1j} = \beta_{1j} \sum_{k=t-t_0}^{\infty} \theta(1-\theta)^{k-t+t_0}(S_{t-k-1}+S^{**}_{t-k-1})$$

and

$$m^{**}_{t} = S^{*}_{t} + \sum_{k=0}^{t-t_0-1} \theta(1-\theta)^{k}(S_{t-k-1}+S^{**}_{t-k-1})$$

A_{tj} = acreage planned for use in the production of the j^{th} crop,

$(1-\theta)^{t-t_o}$ = the influence of prices, yields, and stochastic (not known until after decisions are made) subsidies and taxes observed prior to t_o,

m_t^{**} = the influence of prices, yields, stochastic and nonstochastic (announced before decisions are made) subsidies and taxes observed since t_o,

S_t = vector of prices and yields observed in period t,

S_t^* = vector of nonstochastic subsidies and taxes for period t,

S_t^{**} = vector of stochastic subsidies and taxes for period t

I_t^* = vector of allotment indicators times the respective rate of participation,

d_t^{**} = vector of allotment levels times the respective rate of participation,

ψ_t^* = vector of price support levels times the respective rate of participation when respective allotments are established; vector of price support levels when respective allotments are not established,

d_{tj}^+ = acreage diverted under the government program for crop j,

and

ε_{tj} = stochastic disturbance in the j^{th} acreage decision.

Alternative models with some restrictions were also presented and discussed in Just (16). The general model is the model presented herein with no constraints on the model. Because of the government program, data is often very highly correlated so that little or no significance can be indicated in estimation, alternatives models (Models 2, 3 and 4) were presented as the general model with more restrictions. The restrictions to the general model for Models 2, 3, 4 were described as follows:

1) Model 2: Diversion highly correlated with participating allotment, i.e.

$$d_{tj}^{+} \approx \bar{b}_{4j} d_t^{**} \tag{2.33}$$

2) Model 3: Participating allotment highly correlated with participation, i.e.

$$d_t^{**} \approx \bar{b}_2 I_t^{*} \tag{2.34}$$

3) Model 4: Diversion, participation, and participating allotment all mutually highly correlated, i.e.,

$$d_{tj}^{+} \approx \bar{b}_{4j} d_t^{**}$$

$$d_t^{**} \approx \bar{b}_2 I_t^{*}$$

For empirical analysis in Just's study, the general model was utilized first; then, alternative models were considered and estimated. The most appropriate models were used in presenting the results and in discussing the effect of the government programs.

The results of the study of acreage response in the San Joaquin Valley, 1949-1970, were reasonable in almost every case for price support and allotment variables. For crops where CCC acquisitions have been negligible and production has not been controlled by voluntary allotments, significance of price-support levels could not be shown. For crops controlled by voluntary allotments, price-supports were sometimes important even where CCC acquisitions were negligible because sizable direct support payments were made to compliers. The allotment variables also performed well for the crops controlled by strict allotments. The effect of the diversion variables could also not be isolated in most cases. For feed grain programs, the effect of diverted acreage is probably carried in the allotment participation variables as would occur in the case of Model 4 (16, pp. 450-451).

With regard to the interdependencies of government programs in supply response, production projections of feed grains in the San Joaquin Valley appear to depend very heavily on the continuation of the cotton program as well as the feed grain programs. These results suggested that, in forecasting supply of products, information on the existing and anticipated government programs would be useful and should be utilized (16, p. 451).

The most interesting model in which linear regression analysis is used for evaluating farm commodities programs is that of Houck and Ryan (10). The model was utilized for analyses of acreage supply relationships of corn by Houck and Ryan (10) and by Ryan and Abel (27); for soybeans by Houck and Subotnik (11) and Houck, Ryan and Subotnik (12); for sorghum by Ryan and Abel (29); and for oats and barley by Ryan and Abel (28). The general statement of the economic model in these analyses is expressed as follows:

$$A = f(G,M,Z); \tag{2.35}$$

where

A represents acreage planted of the crop under study,

G represents government policy programs such as price support loan rates, direct payments and diversion payments, with reference to the crop being studied and related crops,

M represents market influences,

Z represents all other supply determinants and random effects.

Consider the components of the government policy variables. The notion of a weighted support rate for policy-influenced crops was introduced in those studies. The weighted price support rate was developed as a means of incorporating both acreage restrictions and announced price supports into a single variable. This means that the variable affecting the acreage planted is the weighted price support rate, not the announced price support rate. The weighted price support rate is a function of the announced price support rate, with some weight, i.e.

$$PF = r \cdot PA \tag{2.36}$$

where PA is the announced price support rate, r is the adjustment factor, and PF is the weighted price support rate. The problem is finding the appropriate adjustment factor to apply to PA to bring it to PF for any set of program provisions. This adjustment factor, in Houck and Ryan's notion, is a measure of the acreage restricting features of a particular program. Generally, the range of r is between 0 and 1.0. If no restrictions are attached to the PA, then r is 1.0 and PA is the same as PF. The tighter the restrictions, the closer r will be to zero.

In addition to acreage restriction and price support loan rate, the existence of diversion payments as another program might be included. Diversion payments represent payment for diverting land from production of the crop under study to other crops. In empirical work, the diversion payment variable was measured by a weighted support loan rate, i.e.

$$DP = w.PR \qquad (2.37)$$

where DP is diversion payment, w is a weight to account for restrictions on the use of diverted land and PR is the payment rate of diverted land.

The supply relationship generally does explicitly include lagged or expected market prices as in Nerlove's Model in Nerlove (21). Therefore, in general, the market variables might be included in the supply response equation. As a matter of fact, the acreage response of a crop will depend either on policy variables or market variables of that particular crop. In a previous study, Ryan and Abel (29) found that policy variables were more effective for sorghum supply response. They regressed sorghum acreage planted upon lagged market prices, weighted diversion payment rate and the other variables. The policy variables were significant, but the market variable (lagged market prices) was not. The policy variables were also considered as effective variables in the supply response studies for corn by Houck and Ryan (10) and by Ryan and Abel (27); and for oats and barley by Ryan and Abel (28). However, the market variable was considered as an effective independent variable included in the supply response for soybeans by Houck and Subotnik (11). In the empirical analysis of this study, both types of variables will be observed and taken into account.

In conclusion, the government farm programs will affect farmers decisions. Some government farm programs, such as the land allotment program, have a direct effect, and some have an indirect effect via the return expected by the farmers. In a more general economic model, the relationship could be presented as follows:

$$A_{tj} = F(\hat{P}, \hat{y}, \overline{G}, \hat{G}) \qquad (2.38)$$

Where

A_{tj} = acreage planned in the production of j^{th} crop,

$\hat{P}$ = the expectation of prices (own prices and other products prices)

$\hat{y}$ = the expectation of yields,

$\overline{G}$ = the government program known in the decision period,

$\hat{G}$ = the expectation of some government policy in the near future during the producing and marketing period.

D. Modigliani and Cohen Model Concerning Analytical Uses of Subjective Data (20)

In Sections A to C, economic models of farm firm decision-making have been developed. In this section, the systematic approach to utilizing the subjective variables of Modigliani and Cohen will be presented. Modigliani and Cohen discuss the role of subjective data in economic analysis and forecasting. They focus on analyzing behavior during period t; this requires some consideration of anticipations and plans made during previous periods.

Let us consider the problem of the farm firm as seen at the beginning of planting season. The number of acres the firm intends to plant to a crop can be regarded as the solution of a constrained maximization problem; it is some function of the initial conditions and the anticipated future conditions (i.e., government policy, expected prices etc.). Now, the anticipated constraints for the future period depend only on the initial conditions at the time of planning and the anticipated behavior of the environment during the period. Let

C_{t-i} = initial conditions, conditions prevailing during period t-i for i = 1,2,3,... .

B_t = actual environmental behavior during period t.

${}_{t-1}B_{(t+k)}$ = anticipations formed during period t-1 (base date) concerning environmental behavior during period t+k for k = 1,2,...,K.

K = length of relevant anticipations time horizon.

The anticipations function relates a firm's anticipations about the future to initial conditions. Denoting the anticipations function for relevant environmental behavior k periods ahead by A_k, we have

$$ {}_{t-1}B_{(t+k)} = A_k[C_{t-i}] \quad k = 0,1,\ldots,K \quad i = 1,2,3,\ldots \quad (2.39) $$

In practice, the anticipation for any particular aspect of environmental behavior might be simple, perhaps consisting of a constant level, the projection of trend, or some simple learning mechanism; or, on the other hand, it might be complex. Examples of some price and yield expectation functions can be seen in Behrman (3).

Let

X_{jt} = farm firm's behavior during period t, i.e. actual acreage planted in crop j,

${}_{t-1}X_{jt}$ = decisions made in period t-1 as to behavior in period t, i.e. intended acreage in planting crop j.

The decision function relates decisions to initial conditions and to anticipated future environmental behavior:

$${}_{t-1}X_t = \text{vector of } {}_{t-1}X_{jt}$$

$${}_{t-1}X_t = D_{t-1}(C_{t-1}, {}_{t-1}B_{(t)}, \cdots {}_{t-1}B_{(t+K)}). \tag{2.40}$$

D, the decision function, is a vector. In this study, D is the same as the supply response function derived from the previous model (i.e., Model of (2.38)). In particular, it depends on anticipation of prices and yields of the farmers, and they in turn depend on the initial conditions.

The firm may not be able to carry out all of its decisions. The actual set within which the firm's behavior must lie is a function of the initial conditions and of the actual relevant environmental behavior during that period. Inasmuch as the anticipated and actual environmental behaviors may differ, the anticipated constraints may not be the same as the actual constraints. Thus the decisions may have to be adjusted. We can formalize this concept by introducing the realization function as follows (letting X_t = vector of X_{jt}):

$$X_t = R_t({}_{t-1}X_t, C^*_{t-1}, {}_{t-1}B_t, B_t) \tag{2.41}$$

accounts for relation between plans and actual behavior, where

C^*_{t-1} = initial condition affecting realization.

An equation that relates actual acreage to planted acreage and other variables is a realizations function. This study deals with estimation of realization functions.

In the preceding analysis of Section C, the course of the economy is regarded as being determined by a system of simultaneous behavior functions, one for each farm firm, defined over a time interval of a year. No practical forecasting procedure could ever be based on such a system of equations. Any complex economic system, such as that of the U.S. farm economy, is comprised of millions of decision-making farms. The empirical task of obtaining estimates of the behavior functions of each farm would be hopelessly impossible, even with the large capacity electronic computers presently available. With the introduction of the concept of temporal aggregates, a further degree of approximation could be introduced into the model of Section D when it is interpreted as applying to aggregates of decision-making farm firms. Although there are some "problems of aggregation" involved in the aggregation, Modigliani and Cohen regard them as beyond the scope of their study.

E. Model Specification of Present Study

The present study will attempt to expand and revise the acreage response model of Houck and Ryan and others so that it will include subjective variables. The basic model to be used in this study is a slight modification of the Houck and Ryan model. The expected yields of own crop and competitive crops are added to the Houck and Ryan model. This basic model will be revised by taking into account the Modigliani and Cohen analytical techniques. The models will encompass six annual crops: (1) corn, (2) soybeans, (3) sorghum, (4) oats, (5) barley, and (6) wheat. The models will be presented in this section in general form. The related studies will be presented in Section E.1. The basic model (model without subjective variables) and revised model (model with subjective variables) will be presented in Sections E.2 and E.3 respectively.

1. Related studies

In 1972, Houck and Ryan (10) analyzed the equations for corn acreage planted in the U.S. from 1948-1970. Several nationwide corn acreage planted equations were estimated by least squares. They used corn acreage planted as a dependent variable. The weighted loan rate, weighted diversion payment, price support for soybeans, U.S. acreage planted for sorghum and time trend were independent variables. Generally speaking, the signs of the estimated coefficients are consistent with prior expectation and are significant. The overall fit of the equations, indicated by R^2, which range from 0.960 to 0.983, is good. Corn policy variables contributed importantly to the changes in acreage planted.

Later in the same year, Ryan and Abel (27) modified Houck and Ryan model to analyze the effect of the set-aside program on corn planting. The results of the second study were consistent with the former, with the policy variables contributing importantly to the change in acreage planted. In addition, these studies showed that soybeans competed with corn for production resources.

Houck and Subotnik (11) and Houck, Ryan and Subotnik (12) studied the acreage planted response for soybeans for six regions in the U.S. In contrast with the corn studies, the results of this study show that market variables play an important role in production decisions for soybean planting. The market-price elasticities were generally larger than the effective support-price elasticities. In addition, corn acreage was closely related to soybeans acreage.

In 1973, Ryan and Abel (29) utilized the Houck and Ryan model to evaluate the impact of price-support programs on sorghum acreage. The policy variables used to represent the effect of price-support programs on sorghum acreage are highly significant. The other variables used to explain the variations in sorghum acreage planted are lagged market price, acreage of winter wheat planted in some states, acreage of corn planted in some states, acreage of cotton planted in some states, and time trend. The results show that lagged market prices were not a significant variable. In summary, the results were generally similar to the earlier ones for corn. The crops competing with sorghum are cotton, wheat and soybeans. There was no significant measure of the substitution between corn and sorghum in this study. The model also appears to be useful for forecasting purposes.

In the latter part of 1973, Ryan and Abel (28) published the study of the other two feed grains, oats and barley. Following the same theoretical analysis, acreage response equations for oats and barley were estimated by least squares. The study periods were 1956-1971 for oats and 1948-1971 for barley. Policy variables included in most of the equations are the support price variables. Because no acreage restrictions applied to oats, the price support loan rate is the variable used in the oat model. For barley, the support loan rate was adjusted to obtain a weighted support loan rate. Diversion payment for barley was used in the barley model. Since there were no diversion programs for oats, there was no corresponding variable for oats. The results of the study show that the policy variables employed for oats and barley are significantly related to acreage planted. The models were used to forecast acreage planted in the following year. The results of forecasting lent support to the usefulness of the equations for oats and barley presented in the study.

In 1976, U.S.D.A., in cooperation with the University of Minnesota Agricultural Experiment Station (32), published a study of four feed grains and the other three crops, wheat, soybeans and cotton. Most of the analyses in the USDA study related to the previous works cited above. The new concepts introduced therein were the use of spliced variables and price ratios to capture the effects of the changed economic setting in crop production. For each of the feed grains, since 1971, acreage restraints have been removed, and market prices have been considerably above support level. The use of "spliced" variables was because of the approximate expected prices or supply-inducing prices which induced the farmers to respond.

Those approximate supply-inducing prices were composed of weighted support loan rates and lagged market prices. This notion leads to the construction of new variables shown as $PICN_t$, $PIBY_t$, $PIGM_t$ and $PIOT_t$, which refer to supply-inducing prices for corn, barley, sorghum and oats, respectively. These new variables are the weighted support loan rates for corresponding crops in 1950 to 1971 and the lagged market prices for corresponding crops in 1972-1974.

For the wheat study, the supply-inducing price variable was derived as expected prices which were considered to be a weighted combination of a simple lagged-market prices and weighted price support variable. The price expectations relationship was expressed as:

$$P_t^* = (w_1 PWT_{t-1} + w_2 PFWT_t) \tag{2.42}$$

where

P_t^* = producer prices expectation for wheat in year t,

PWT_{t-1} = lagged wheat average prices received by farmers,

$PFWT_t$ = effective price support for wheat in year t,

w_1 = weight associated with PWT_{t-1},

w_2 = weight associated with $PFWT_t$.

In the case of wheat, the participation rate is the proportion of wheat planted subject to direct benefits or to program provisions. This rate remained fairly constant over time. Therefore, it was assumed that weights derived from regression analysis, w_1 and w_2, indicate the market price influences and program provisions. Both variables of PWT_{t-1} and $PFWT_t$ were used as explanatory variables in the wheat-supply model.

The expected price for soybeans in the USDA study was also considered as a weighted combination of a single lagged market prices and a weighted support-prices variable. Since no acreage restraints have been used on soybeans, the value of PFSB was equal to PSSB and r = 1.0. Therefore, two variables of PSB_{t-1} and $PSSB_t$ were used in the soybeans-supply response model in this study. The other explanatory variables were the same as those used in previous studies.

2. Basic model of acreage response relations of six annual crops

From the theoretical analysis in Section II.C, the general linear model in this study will be constructed as follows:

Model I: Basic Model

$$AP_i = F_1(PF_i, DP_i, P_{t-1,i}, PF_j, P_{t-1,j}, YE_i, YE_j, \text{OTHERS}) \quad (2.43)$$

where

AP_i = actual planted acreage for crop i,

PF_i = U.S. average weighted loan rate for crop i,

DP_i = acreage diversion rate for crop i,

$P_{t-1,i}$ = average market prices received by farmers for crop i, lagged one year,

PF_j = U.S. average weighted loan rate for crop j (competitive crop),

$P_{t-1,j}$ = average market prices received by farmers for crop j (lagged one year),

YE_i = expected yield of crop i,

YE_j = expected yield of crop j (competitive crop),

OTHERS = dummy variable and/or time trend.

This model is called a basic model in the sense that there is no subjective variables included in the model. It is modified from Houck and Ryan's Model which is based on the theoretical analysis in Section A to B. The only difference from their model is the inclusion of expected yields as additional independent variables.

3. Revised model with subjective variables

With reference to the theoretical analysis of Modigliani and Cohen in Section D, the realization function approach or semi-causal forecasting will be utilized in empirical study. For the case of building an economic model to forecast farm crops, if data on farmers' intention to plant and their actual plantings are available, econometric forecasting models need to consider only the realization function and can ignore the anticipation function and decision function.

From this point, the realization function of (2.41) in this study will be presented as an estimable linear statistical relationship as follows:

Model II: Revised Model (Model with subjective variables)

$$AP = F_2(AI_i, AI_j, PF_i, DP_i, P_{t-1,i}, PF_j, P_{t-1,j}, YE_i, YE_j, \text{OTHERS}) \qquad (2.44)$$

where

AI_i = intention acreages of planting crop i,

AI_j = intention acreages of planting crop j (competitive crop),

others are the same as variables in Model I.

Two other additional models will be presented here. These two models are obtained from Model II, by eliminating some variables, and they provide the tests of significance of coefficients of some groups of variables. The significance test will provide the evidence for concluding which model has a superiority in estimating and forecasting performance.

Two additional models follow:

Model III:

$$AP_i = F_3(AI_i, PF_i, DP_i, P_{t-1,i}, PF_j, P_{t-1,j}, YE_i, YE_j, \text{OTHERS}) \tag{2.45}$$

Model IV:

$$AP_i = F_4(AI_i) \tag{2.46}$$

Where all variables named here are the same as above. The specific models of six crops will be presented in Chapter IV.

Model III is obtained from Model II by dropping intended acreages of competitive crops.

Model IV is obtained from Model II by dropping the intended acreages of competitive crops and all objective variables.

III. STATISTICAL CONSIDERATION

The objectives of econometrics are the production of quantitative economic statements that either explain the behavior of economic phenomena or that forecast behavior or both (4, p. 4). Chapter II of this study derived a quantitative economic statement of the supply response of U.S. major crops. This chapter discusses the appropriate Statistical Model which will be used in estimating the major U.S. crop supplies. Pindyck and Rubinfeld (26, pp. xiii-xv) discussed and presented three econometric models: 1) Time-Series Models, 2) Single-Equation Regression Models and 3) Multi-Equation Simulation Models. They also stated that:

> The choice of the type of model to develop is a difficult one, involving trade-offs among time, energy, costs, and desired forecast precision. The construction of a multi-equation Simulation Model might require large expenditures of time and money, not only in terms of actual work, but also in terms of computer time. The gains that result from this effort might include the better understanding of the relationships and structure involved as well as the ability to make a better forecast. However, in some cases these gains may be small enough so that they are outweighed by the heavy costs involved. Because the multi-equation model necessitates a good deal of knowledge about the process being studied, the construction of such models may be extremely difficult.
>
> The decision to build a time-series model usually occurs in cases when little or nothing is known about the determinants of the variable being studied, however, it may not be obvious whether a time-series model or a single-equation regression model is preferable as a means of forecasting. It may be reasonable for a

> forecaster to construct both types of models and compare their relative performances. . . . Unfortunately, this can be a rather hard problem, as the choice of Model type is often not clear (26, pp. xiv-xv).

However, in this study, the Single-Equation Regression Analysis will be used in estimating the acreage planted response of Model I of (2.43) to Model IV of (2.46). It will also be used in estimating a yield expectation equation and forecasting the expected yield.

Single-Equation Regression Model may be defined as any model in which the variable under study is explained by a single function of explanatory variables. The equation could be linear, quadratic, cubic or another form, or could be time-dependent as is the time index appearing in the model. In this study, the author assumes that the supply response equations is linear. Therefore, Linear-Regression analysis is used in empirical study in this thesis.

A. Single-Equation Linear Statistical Model (15)

The linear statistical model is frequently used in the work of empirical analysis. The classical normal linear regression model can be written in matrix notation as:

$$Y = XB + U \tag{3.1}$$

where

Y = a column vector of n observations on the dependent variable,

X = an n x (k+1) matrix of observations on the k explanatory variables and a column vector of ones,

B = a column vector of (k+1) unknown parameters for which estimates are to be obtained,

U = an nx1 column vector of errors or unknown disturbance terms.

In estimating the vector of parameter B, we must make some assumptions about the Equation (3.1). The assumptions are crucial for the processes of estimating and making inferences. The assumption set is

$$E(U) = 0 \tag{3.2}$$

$$E(UU') = \sigma^2 I_n \tag{3.3}$$

X is a set of fixed number or is a set of random variables distributed independently of U (3.4)

U is normally distributed, (3.5)

X has rank k+1 < n.

1. O.L.S. estimation method

From (3.1) to (3.5), we can apply the least square method to estimate the parameters of (3.1). Let $\hat{\beta}$ be a column vector of estimated values of B, and e be the column vector of residuals. We then have

$$Y = X\hat{\beta} + e \tag{3.6}$$

From Equation (3.6), by the least squares error criterion, $\hat{\beta}$ is obtained by differentiating e'e with respect to $\hat{\beta}$ and setting the result equal to zero. This will yield the normal equation first, and then the estimator will be obtained by equations:

$$\hat{\beta} = (X'X)^{-1}(X'Y) \tag{3.7}$$

and the corresponding residuals or estimates of errors are:

$$e = Y - X\hat{\beta} \tag{3.8}$$

These estimates can be obtained when given

$$\text{rank } X = k+1 < n \tag{3.9}$$

and therefore, the inverse of (X'X) exists.

The estimate, $\hat{\beta}$, can be shown to be the best linear unbiased estimator (BLUE) of B if the assumptions of (3.2) to (3.4) hold. It can be shown as follows:

$$\begin{aligned}\hat{\beta} &= (X'X)^{-1}X'Y \\ &= (X'X)^{-1}X'(XB+U) \\ &= B + (X'X)^{-1}X'U \end{aligned} \tag{3.10}$$

Taking the expected value of (3.10) yield

$$E(\hat{\beta}) = E(B) + E(X'X)^{-1}X'U = B \tag{3.11}$$

The variance-covariance matrix of $\hat{\beta}$ is

$$V(\hat{\beta}) = E[(\hat{\beta}-B)(\hat{\beta}-B)']$$
$$= \sigma^2(X'X)^{-1} \tag{3.12}$$

The linearity property indicates that the estimators are linear functions of Y as shown by (3.7). The estimators possess a smaller variance than any other linear unbiased estimators. Therefore, we call them best linear unbiased estimators (BLUE).

The expected value of the squared residuals is

$$E(U'U) = \sigma^2(n-k-1) \tag{3.13}$$

so that an unbiased estimator of σ^2 is

$$S_e^2 = e'e/n-k-1 \tag{3.14}$$

2. Significance tests of coefficients B

The estimation procedure and the proof that $\hat{\beta}$ is BLUE do not need the assumption of normality. We need the assumption of the e_i to be normally distributed i.e. (3.5) for performing the significance tests and confidence intervals for the $\hat{\beta}$. Under the normal distribution assumption, the significance tests will hold exactly. By making no explicit assumption about the form of the distribution of the e_i and appealing to the Central Limit Theorem the tests can be regarded as approximately correct (15, p. 135). The assumptions (3.2, 3.3 and 3.5) can be written as

$$e_i \sim N(0,\sigma^2 I_n) \tag{3.15}$$

In performing significance tests, the hypotheses may consist of values of single parameters or of values of sets of parameters or of restrictions on parameters. Testing a hypothesis on a partition of parameters is considered first, the others will be derived from this general case. Excellent discussions of the appropriate statistical tests and procedures are presented in many sources (e.g., 15 and 31) and will not be discussed here in detail.

Suppose the independent variables are divided into two groups, and we are interested in testing the hypothesis that some of the β's are given constants. Considering the linear model expressed as

$$Y = X_1 B_1 + X_2 B_2 + U \tag{3.16}$$

where X_2 is an (nxh) and X_1 is an nx(k+1-h) matrix of independent variables in the model: $X \equiv (X_1 : X_2)$.

We want to test H_o: $B_2 = \lambda_2$. (3.17)

From the model of (3.16) we will obtain:

$$\hat{\beta} = \begin{bmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \end{bmatrix} \sim N\left[\begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix}, \sigma^2 \begin{pmatrix} X_1'X_1 & X_1'X_2 \\ X_2'X_1 & X_2'X_2 \end{pmatrix}\right]^{-1} \tag{3.18}$$

i.e.,

$$\hat{\beta}_2 \sim N[\beta_2, \sigma^2 (X_2' M_1 X_2)^{-1}] \tag{3.19}$$

where

$M_1 = I_n - X_1(X_1'X_1)^{-1}X_1'$.

Now, assuming $U \sim N(0, \sigma^2 I_n)$, we can construct an F-statistic to test the H_0: $\beta_2 = \lambda_2$ as follows:

$$F = \frac{(\hat{\beta}_2-\lambda_2)'(X_2'M_1X_2)(\hat{\beta}_2-\lambda_2)/h}{e'e/(n-k-1)} \tag{3.20}$$

The ratio has an F-distribution with (h, n-k-1) degrees of freedom.

In practice, if we want to test the null hypothesis

H_o: $B_2 = 0$.

The procedure is:

1) Regress Y on $(X_1:X_2)$; get Residual Sum of Squares (Full Model).

2) Regress Y on X_1; get Residual Sum of Squares (Reduced Model).

3) Divide the difference by h.

4) Divide the Mean Square of (3) by the Residual Mean Squares (Full Model).

5) If the value obtained in (4) is greater than the appropriate critical value for F(h,n-k-1), then reject H_0: $B_2=0$.

The above process can be written for testing H_0: $B_2=0$,

$$F_{(h,n-k-1)} = \frac{(SS_{\text{reduced model}}-SS_{\text{full model}})/h}{SS_{\text{full model}}/n-k-1} \tag{3.21}$$

where

$SS_{\text{reduced model}}$ = Residual Sum of Squares of reduced model,

$SS_{\text{full model}}$ = Residual Sum of Squares of full model.

The other method of calculation of F-ratio is

$$F_{(h,n-k-1)} = \frac{R^2_{\text{full model}} - R^2_{\text{reduced model}}/h}{(1-R^2_{\text{full model}})/n-k-1} \tag{3.22}$$

where

$R^2_{\text{full model}}$ = multiple determination of full model,

$R^2_{\text{reduced model}}$ = multiple determination of reduced model.

If we want to test the null hypothesis that all coefficients except the intercept term of the (3.1) equal zero, that is, to test

$B_1 = B_2 = B_3 = \ldots = B_k = 0,$[1] we use an F-ratio.

This F-ratio can be written as

$$F = \frac{R^2_{k+1}/k}{(1-R^2_{k+1})/n-k-1} \tag{3.23}$$

where

$$R^2_{k+1} = \frac{\hat{\beta}'X'Y-(\Sigma Y)^2/n}{Y'Y-(\Sigma Y)^2/n}$$

The ratio value has an F-distribution with (k,(n-k-1)) degrees of freedom.

---

[1] $X_0 = 1$ for all observations.

In a case in which only one independent variable is tested, the null hypothesis in this case will be:

H_o: $B_i = \bar{B}_i$ (i.e. $\bar{B}_i$ might be zero or any constant).

The t-student statistic will be

$$t = \frac{B_i - \bar{B}_i}{\sqrt{\frac{1}{n-k-1}\left(\sum_{i=1}^{n} e_i^2\right) a_{ii}}} \tag{3.24}$$

where a_{ii} is the i^{th} diagonal element in $(X'X)^{-1}$, and t has student t distribution with (n-k-1) degrees of freedom. In this special case, F-ratio with (1, n-k-1) degrees of freedom is equivalent to t^2 (n-k-1) ratio.

3. Forecasting with a single-equation regression model

The purpose of constructing and estimating the relations in the last section is for forecasting or prediction. Pindyck and Rubinfeld (26, p. 156) define a forecast as a quantitative estimate (or set of estimates) about the likelihood of future events based on past and current information. They also distinguish between two types of forecasting; *ex post* and *ex ante*. An *ex post* forecast predicts the values of endogeneous variables in the sampling period when both endogeneous and exogeneous variables are known already. It can be used to check against existing data and provide a means of evaluating a forecasting model. An *ex ante* forecast predicts values of the dependent variable beyond the estimation period, using explanatory variables which may or may not be known with certainty (26, p. 157).

B. Violations of the O.L.S. Model Assumptions

1. Multicollinearity

Intercorrelation among the independent variables is referred to as multicollinearity. In this study, where actual acreage planted is the dependent variable, the intended acreage might be highly intercorrelated with the other independent variables. Perfect multicollinearity violates condition (3.9) and prevents the solution of the O.L.S. estimators. However, it more commonly happens that some independent variables are highly but not perfectly correlated. Under these conditions $(X'X)^{-1}$ exists but its terms are likely to be quite large, and a coefficient which was thought to be negative may be estimated by a large positive, nonsignificant number. Johnston (15) gave the following difficulties of the effects of multicollinearity:

1. The precision of estimation falls so that it becomes very difficult to disentangle the relative influences of the various independent variables. This loss of precision has three aspects: specific estimates may have very large errors; these errors may be highly correlated one with another; and the sampling variances of the coefficients will be very large.

2. Investigators are sometimes led to drop variables incorrectly from an analysis because their coefficients are not significantly different from zero, but the true situation may not be that a variable has no effect but simply that the set of sample data has not enabled us to pick it up. The investigator has the choice of presenting the results and stating that the data are inadequate to permit reliable estimation.

3. Estimates of coefficients become very sensitive to particular sets of sample data, and the addition of a few more observations can sometimes produce dramatic shifts in some coefficients (14, pp. 29-39).

Tests of the presence of multicollinearity require the judicious use of various correlation coefficients. In the case of two independent variables, the simple correlation coefficient suffices. When there are more than two independent variables, both zero-order and partial correlation coefficients should be examined, but even these may not be sufficient indicators. A more generally reliable guide, therefore, may be obtained by considering the coefficient of multiple determination, R_i^2, between each X_{ij} and the remaining (k) variables in X (5, pp. 92-107).

Suggested solutions for multicollinearity follow:

1. Add outside information to the estimation procedure. This approach requires either more data or some knowledge of

the coefficients. As a matter of fact, the economist often have some information on the nature of the coefficients in the model. One approach followed often in practice is to drop one or more of the highly correlated independent variables from the equation. This is equivalent to setting the coefficient for that variable equal to zero. If other information is known to the researcher, the linear transformation or restricted least square approach might be used to solve the problem. For details of linear transformation method, see Fuller (6).

2. If we have pair-wise multicollinearity, we might regress this pair separately first, then use the residuals from this regression to represent the variable treated as the dependent one. This method will insure that the residual and the variable treated as independent variable are independent. In this thesis, the realization function contains the intention variable and other variables explaining the realization variable. The intention variable might be highly intercorrelated with the others. To utilize the intention variable in the analysis, we might regress this upon the other variables and use the residual as an independent variable in estimating the realization function. The use of this procedure would reduce the collinearity of the intention variable with the others.

2. Autocorrelated errors

In time-series data, the correlation of the error term U with previous values of itself is referred to as autocorrelated errors. Autocorrelated errors are a special case of serially correlated errors. Serially correlated errors refers to the case in which error terms may be correlated with past values of themselves and/or errors in other equations. The correlation between the errors of two or more equations will be considered in the next section. The presence of the autocorrelated errors violates the O.L.S. model assumption that successive disturbances are independent, assumption (3.15). This assumption implies that $E[U(t)U(t-j)] = 0$ for all j not equal to zero and over all t. Johnston (15, pp. 243-244) noted that there are several circumstances in which the assumption of a serially independent disturbance term may not be met. One of these is an incorrect specification as to the form of the relationship between the dependent and the independent variables. This can arise from incorrect model specifications which omit a relevant independent variable from the analysis. If there is serial correlation among these omitted variables that does not cancel out, autocorrelation is the possible result. A second possible explanation for the presence of autocorrelated errors is measurement errors on the variables in the analysis.

The consequences of autocorrelated errors in the O.L.S. model are numerous (15, pp. 246-249 and 26, pp. 197-198). First, if there is no lagged dependent variable appearing as an independent variable in the model, we will obtain unbiased estimators of B, but they will not be efficient. Second, the estimates of the coefficients' sampling variances are also likely to be underestimated and the t and F test will be biased. Third, inefficient predictions, that is, predictions with needlessly large sampling variances, will be obtained. When the model specification leads to the inclusion of lagged dependent variables as independent variables --as in the reduced form of Nerlovian supply response equation, then $\hat{\beta}$ is biased and inconsistent.

There are several tests based on the residual vector of U which are commonly used to determine the presence of autocorrelated errors. These tests are the Durbin-Watson d statistic, the Theil-Nagar d and the Hart-von Neuman ratio. Those tests appear in most econometric textbooks, including Johnston (15, pp. 249-254). However, Ladd (19, p. 332) pointed out that the use of residuals to compute the autoregressive properties of errors is not a satisfactory method.

3. Inter-group correlation in errors

In this study, there are several sets of data or several supply response equations used in estimating coefficients. One assumption in using O.L.S. for each set of data is that the errors are uncorrelated between groups. However, the errors might be correlated between groups or equations; i.e. the errors for the supply response equation for corn are correlated with errors for the supply response equation for soybeans. If correlation among the groups of data exist, the seemingly unrelated regressions of Zellner (39) are suggested. Ladd (18) suggests that having a test for $U_{ij}=0$, where U_{ij} is the errors among groups or equations, is therefore desirable. Such test can be derived from Anderson (2, pp. 61-66).

Two versions of the procedure of estimating parameters associated with sets of seemingly unrelated regression equations will be considered and reviewed here. One version is the estimation procedure with the assumption that there is no autocorrelation in each equation. This version can be seen in Zellner (39, pp. 349-352) and Zellner and Huang (40, pp. 300-303). The other version is the estimation procedure with the assumption of autocorrelation in each equation, as seen in Parks (24, pp. 500-504) and Kmenta and Gilbert (17, pp. 186-189).

a. <u>Estimation procedure of seemingly unrelated regression</u> (39) Let the set of equations be written as:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_M \end{bmatrix} = \begin{bmatrix} X_1 & 0 & 0 \cdots & 0 \\ 0 & X_2 & 0 \cdots & 0 \\ & & & \\ 0 & 0 & 0 \cdots & X_M \end{bmatrix} \begin{bmatrix} B_1 \\ B_2 \\ \\ B_M \end{bmatrix} + \begin{bmatrix} U_1 \\ U_2 \\ \\ U_M \end{bmatrix} \qquad (3.25)$$

or

$$y = XB + U,$$

where

y_m is a Tx1 vector of observations on the m^{th} dependent variable,

X_m is a Txk_m matrix of rank k_m of observations on k_m "independent" variables,

B_m is a $k_m x1$ vector of coefficients,

and

U_m is a Tx1 disturbance vector.

We assume that $E(U_m) = 0$, $m = 1,2,\ldots,M$, and that the disturbance variance-covariance matrix is given by

$$\Sigma = E \begin{bmatrix} U_1 \\ U_2 \\ \vdots \\ U_M \end{bmatrix} (U_1' U_2' \cdots U_M') = \begin{bmatrix} \sigma_{11}I & \sigma_{12}I & \cdots & \sigma_{1M}I \\ \sigma_{21}I & \sigma_{22}I & \cdots & \sigma_{2M}I \\ \vdots & \vdots & & \vdots \\ \sigma_{M1}I & \sigma_{M2}I & \cdots & \sigma_{MM}I \end{bmatrix}$$

$$= \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1M} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{M1} & \sigma_{M2} & & \sigma_{MM} \end{bmatrix} \otimes I = \Sigma_c \otimes I, \qquad (3.26)$$

where the unit matrices are of size TxT, and $\sigma_{mm'} = E[U_{mt}U_{m't}]$ for $t = 1,2,\ldots,T$.

This form implies the absence of serial and autocorrelation.

The inverse of Σ is

$$\Sigma^{-1} = \begin{bmatrix} \sigma^{11}I & \sigma^{12}I & \cdots & \sigma^{1M}I \\ \sigma^{21}I & \sigma^{22}I & \cdots & \sigma^{2M}I \\ \vdots & \vdots & \ddots & \vdots \\ \sigma^{M1}I & \sigma^{M2}I & \cdots & \sigma^{MM}I \end{bmatrix}$$

$$= \begin{bmatrix} \sigma^{11} & \sigma^{12} & \cdots & \sigma^{1M} \\ \sigma^{21} & \sigma^{22} & \cdots & \sigma^{2M} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma^{M1} & \sigma^{M2} & & \sigma^{MM} \end{bmatrix} \otimes I, \qquad (3.27)$$

Now, we apply Aitken's generalized least squares to obtain the Aitken estimator:

$$\beta^* = \begin{bmatrix} \beta_1^* \\ \beta_2^* \\ \vdots \\ \beta_M^* \end{bmatrix} = (X'\Sigma^{-1}X)^{-1}(X'\Sigma^{-1}Y), \tag{3.28}$$

Thus we have

$$\beta^* = \begin{bmatrix} \beta_1^* \\ \beta_2^* \\ \vdots \\ \beta_M^* \end{bmatrix} = \begin{bmatrix} \sigma^{11}X_1'X_1 & \sigma^{12}X_1'X_2 & \cdots & \sigma^{1M}X_1'X_M \\ \sigma^{21}X_2'X_1 & \sigma^{22}X_2'X_2 & \cdots & \sigma^{2M}X_2'X_M \\ \vdots & \vdots & \ddots & \vdots \\ \sigma^{M1}X_M'X_1 & \sigma^{M2}X_M'X_2 & \cdots & \sigma^{MM}X_M'X_M \end{bmatrix}^{-1} \begin{bmatrix} \sum_{m=1}^{M} \sigma^{1M}X_1'Y_M \\ \vdots \\ \sum_{m=1}^{M} \sigma^{M}X_M'Y_M \end{bmatrix} \tag{3.29}$$

and the variance-covariance matrix of estimator β^* is

$$V(\beta^*) = \begin{bmatrix} \sigma^{11}X_1'X_1 & \sigma^{12}X_1'X_2 & \cdots & \sigma^{1M}X_1'X_M \\ \sigma^{21}X_2'X_1 & \sigma^{22}X_2'X_2 & \cdots & \sigma^{2M}X_2'X_M \\ \vdots & \vdots & \ddots & \vdots \\ \sigma^{M1}X_M'X_1 & \sigma^{M2}X_M'X_2 & \cdots & \sigma^{MM}X_M'X_M \end{bmatrix}^{-1} \tag{3.30}$$

Since the matrix Σ is generally unknown, in application we utilize single-equation least-squares residuals to estimate it and its inverse.

That is, we construct from single-equation least-square

$$\Sigma_e = \begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1M} \\ s_{21} & s_{22} & \cdots & s_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ s_{M1} & s_{M2} & \cdots & s_{MM} \end{bmatrix} \otimes I \tag{3.31}$$

and

$$\Sigma_e^{-1} = \{s^{mm'}\} \otimes I. \tag{3.32}$$

Then our efficient estimator is given by

$$\hat{\beta} = \begin{bmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \\ \vdots \\ \hat{\beta}_M \end{bmatrix} = \begin{bmatrix} s^{11}X_1'X_1 & s^{12}X_1'X_2 & \cdots & s^{1M}X_1'X_M \\ s^{21}X_2'X_1 & s^{22}X_2'X_2 & \cdots & s^{2M}X_2'X_M \\ \vdots & \vdots & \ddots & \vdots \\ s^{M1}X_M'X_1 & s^{M2}X_M'X_2 & \cdots & s^{MM}X_M'X_M \end{bmatrix}^{-1} \begin{bmatrix} \sum_{m=1}^{M} s^{1M}X_1'Y_1 \\ \\ \vdots \\ \sum_{m=1}^{M} s^{MM}X_M'Y_M \end{bmatrix} \tag{3.33}$$

and

$$V(\hat{\beta}) = \begin{bmatrix} s^{11}X_1'X_1 & s^{12}X_1'X_2 & \cdots & s^{1M}X_1'X_M \\ s^{21}X_2'X_1 & s^{22}X_2'X_2 & \cdots & s^{2M}X_2'X_M \\ \vdots & \vdots & \ddots & \vdots \\ s^{M1}X_M'X_1 & s^{M2}X_M'X_2 & \cdots & s^{MM}X_M'X_M \end{bmatrix}^{-1} + o(T^{-1}) \tag{3.34}$$

where $o(T^{-1})$ denotes terms of higher order of smallness than T^{-1}.

b. Estimation procedure of seemingly unrelated regression with autoregressive errors When there is an autocorrelated error in each equation, the three-stage Aitken Method (ZEF-OLS) has been proposed by Parks (24, pp. 503-504). The first step uses single equation regressions to estimate the parameters of the autoregressive model; the second step uses single equation regressions on transformed equations to estimate the contemporaneous covariances, the third step finally obtains the Aitken estimator.

Consider the i^{th} equation of the regression system (3.25). It is assumed that the disturbances are autocorrelated, i.e.

$$U_{it} = \rho_i U_{i,t-1} + e_{it};\ \rho_i < 1,\quad i = 1,2,\ldots,M \qquad (3.35)$$

where

e_{it} are random variables satisfying the conditions

$E(e_{it}) = 0;\ i = 1,2,\ldots,M;\quad t = 1,2,\ldots,T$

$$\begin{aligned} E(e_{it}e_{jt'}) &= \sigma_{ij} \quad \text{for } i,j = 1,2,\ldots,M, \text{ and } t = t' \\ &= 0 \quad \text{for } i,j = 1,2,\ldots,M \text{ and } t \neq t. \end{aligned} \qquad (3.36)$$

In addition, assume that

$$U_{i1} = \rho_i U_{i0} + e_{i1} \qquad (3.37)$$

where U_{i0} is a random variable drawn from a population with mean zero and variance $\sigma_{ii}(1-\rho_i^2)^{-1}$.

Therefore, the i^{th} equation of the system (3.25) can be written as

$$y_i = X_i B_i + P_i e_i \tag{3.38}$$

where

$$P_i = \begin{bmatrix} (1-\rho_i^2)^{-1/2} & 0 & 0 & \cdots & 0 \\ \rho_i(1-\rho_i^2)^{-1/2} & 1 & 0 & \cdots & 0 \\ \rho_i(1-\rho_i^2)^{-1/2} & \rho_i & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \\ \rho_i^{T-1}(1-\rho_i^2)^{-1/2} & \rho_i^{T-2} & \rho_i^{T-3} & \cdots & 1 \end{bmatrix} \tag{3.39}$$

To estimate the parameters of (3.37), consider $\hat{U}_i = y_i - X_i\hat{B}_i$, where $\hat{B}_i$ is the ordinary least squares estimate of B_i. The parameters, ρ_i, can be estimated on the basis of a regression on these residuals, and the equation

$\hat{U}_{it} = \rho_i \hat{U}_{i,t-1} + e_{it}$ gives

$$\hat{\rho}_i = \frac{\sum_{t=2}^{T} \hat{U}_{it}\hat{U}_{it-1}}{\sum_{t=2}^{T} \hat{U}_{it-1}^2} \tag{3.40}$$

The matrix $\hat{P}_i$ is obtained by substituting $\hat{\rho}_i$ for ρ_i in (3.37).

Transforming by premultiplication of Equation (3.38) by

$\hat{P}_i^{-1}$ gives

$$\hat{P}_i^{-1}y_i = \hat{P}_i^{-1}X_iB_i \,\lrcorner\, \hat{P}_i^{-1}P_ie_i$$

or

$$y_i^* = X_i^*\beta_i + e_i^*, \quad i = 1,2,\ldots,M. \qquad (3.41)$$

By regressing the transformed equation above, the estimated residuals can be used to estimate the elements of the contemporaneous covariance matrix $\Sigma_c = \{S_{ij}\}$ by

$$S_{ij} = \frac{\hat{e}_i'\hat{e}_j'}{(T-k_i)^{1/2}(T-k_j)^{1/2}}$$

$$= \frac{(y_i^*-X_i^*\hat{\beta}_i)'(Y_j^*-X_j^*\hat{\beta}_j)}{(T-k_i)^{1/2}(T-k_j)^{1/2}} \qquad (3.42)$$

where $\hat{\beta}_i$ is the O.L.S. estimators of the i^{th} transformed equation estimation.

Finally, in the third step

$$\tilde{\beta} = (X'\hat{\Omega}^{-1}X)^{-1}X'\hat{\Omega}^{-1}y \qquad (3.43)$$

where

$$\hat{\Omega}^{-1} = \hat{P}'^{-1}\hat{\Sigma}^{-1}\hat{P}^{-1}$$

$$= \hat{P}'^{-1}(\hat{\Sigma}_c^{-1} \otimes I)\hat{P}^{-1} \qquad (3.44)$$

4. Specification errors

Errors in selecting the appropriate set of independent variables contained in the equation are commonly referred to as specification errors. The consequence of those errors are likely to be a biased estimated coefficient and an upward biased estimate of the residual variance. This can be demonstrated through the following.

Suppose that the true model is the equation of (3.1), but we mistakenly select a set of independent variables $\bar{X}$ of order $n x(\bar{k}+1)$ which is some subset of the true model independent variable X. We would then obtain the least squares estimator

$$\bar{b} = (\bar{X}'\bar{X})^{-1}\bar{X}'Y \tag{3.45}$$

and

$$E(b) = (\bar{X}'\bar{X})^{-1}\bar{X}'XB \tag{3.46}$$

which will be biased estimates of the true coefficient, with the extent of the biases depending on the correlations between the included and omitted variables weighted by the omitted true model parameters (15, p. 169).

It is apparent that the omission of relevant variables from a model reduces the explained sum of squares and therefore biases upward the estimate of the residual variance, $\hat{\sigma}_e^2$. This, in turn, inflates the estimated standard errors of the regression coefficients and reduces the value of the test statistics (t and/or F-test) of these coefficients below commonly used critical regions.

Another possible specification error is the presence of an irrelevant variable. The effects of adding an irrelevant variable are quite different from the effects of omitting some variables. We would expect that not taking into account all the information available about the model would lead to a loss of efficiency, but the coefficient is consistent and unbiased. The details of this work are shown in Pindyck and Rubinfeld (26, pp. 189-190).

IV. VARIABLES, DATA, EMPIRICAL MODEL AND PROCEDURE

The discussion contained in the three preceding chapters lays the foundation for analysis of sample data. This chapter will be organized into four sections as follows: (a) variable classification and definitions; (b) data considerations; (c) empirical models; and (d) estimation procedure and methods of analysis.

A. Variable Classification and Definitions

To facilitate further discussion of the empirical models derived from (2.42) to (2.45), the variables used in empirical analysis will be defined in Figure 4.1. The "Variable Name" column which appears on the left side of the figure is an alphameric name. All acreage variables relate to the national or aggregate value. All prices, yields and the other ratio variables relate to the national average. Variables which relate to barley, corn, oats, sorghum, soybeans, wheat and cotton commodities in the model are denoted as BY, CN, OT, GM, SB, WT and CT, respectively. Some other general interpretative guidelines include the following: AP, denotes a planted acreage; AI, March intended acreage; DP, P, PF, PI, and PS, denote diversion payment rates, average market prices, weighted price support rate, supply inducing

VARIABLE NAME	UNIT OF MEASURE	DESCRIPTION
AIBY	thousand acres	March intention acreage of barley
AICN	"	March intention acreage of corn
AIGM	"	March intention acreage of sorghum
AIOT	"	March intention acreage of oats
AISB	"	March intention acreage of soybeans
AIWT	"	March intention acreage of wheat
APBY	"	Planted acreage in barley
APCN	"	Planted acreage in corn
APGM	"	Planted acreage in sorghum
APOT	"	Planted acreage in oats
APSB	"	Planted acreage in soybeans
APWT	"	Planted acreage in wheat
DPCN	$ per bushel	Diversion payment rates for corn
DPGM	$ per bushel	Diversion payment rates for sorghum
DPWT	$ per bushel	Diversion payment rates for wheat
DVEIGH	{ 0; 1952-1967 1; otherwise	Dummy variable to account for a change in oat supply response,
DVSIX	{ 0; 1952-1965 1; otherwise	Dummy variable to account for a change in the method of calculating direct support payments in 1966 and thereafter

Figure 4.1. Variable definitions (Note: the subscripts t and t-1 which stand for current year and lagged one period year will be omitted in this figure)

VARIABLE NAME	UNIT OF MEASURE	DESCRIPTION
PBY	\$ per bushel	Barley market price received by farmers
PCN	"	Corn market price received by farmers
PGM	\$ per cwt.	Sorghum market price received by farmers
POT	\$ per bushel	Oat market price received by farmers
PSB	"	Soybean market price received by farmers
PWT	"	Wheat market price received by farmers
PFBY	"	Weighted support loan rate for barley
PFCN	"	Weighted support loan rate for corn
PFCT	\$ per pound	Weighted support loan rate for cotton
PFGM	\$ per cwt.	Weighted support loan rate for sorghum
PFOT	\$ per bushel	Weighted support loan rate for oats
PFSB	"	Weighted support loan rate for soybeans
PFWT	"	Weighted support loan rate for wheat
PIBY	\$ per bushel	Supply inducing price for barley ($PFBY_t$ for years 1952-1971; PBY_{t-1} for years 1972-1974)
PICN	"	Supply inducing price for corn ($PFCN_t$ for years 1952-1971; PCN_{t-1} for years 1972-1974)
PIGM	\$ per cwt.	Supply inducing price for sorghum ($PFGM_t$ for years 1952-1971; PGM_t for years 1972-1974)
PIOT	\$ per bushel	Supply inducing price for oats ($PFOT_t$ for years 1952-1971; POT_t for years 1972-1974)

Figure 4.1 (Continued)

VARIABLE NAME	UNIT OF MEASURE	DESCRIPTION
PSSB	$ per bushel	Soybean price support loan rate
YBY	bushels per acre	Actual yield of barley
YCN	"	Actual yield of corn
YCT	pounds per acre	Actual yield of cotton
YGM	bushels per acre	Actual yield of sorghum
YOT	"	Actual yield of oats
YSB	"	Actual yield of soybeans
YWT	"	Actual yield of wheat,
YEBY	"	Expected yield of barley
YECN	"	Expected yield of corn
YECT	pounds per acre	Expected yield of cotton
YEGM	bushels per acre	Expected yield of sorghum
YEOT	"	Expected yield of oats
YESB	"	Expected yield of barley
YEWT	"	Expected yield of wheat
T52		Time trend, 1952 = 1, 1953 = 2, 1954 = 3...,
T67		1952 = 1, 1953 = 2,..., 1967 = 16
		0 in 1968, 1969,...,1974

Figure 4.1 (Continued)

prices and announced price support rate; Y and YE denote the actual per acre yield and expected yield of certain commodities.

The second column of Figure 4.1 indicates the units in which the variable is measured. The third column is a brief verbal description of the variable and indicates its empirical counterpart used in the model.

B. Data Considerations

The sample period for estimating the coefficients of all six U.S. farm crops was from 1952 through 1974. This period of time was felt to be sufficiently long to encompass the production cycles for any of the farm crops considered and therefore help capture the essence of the structure of that subsector.

The data sources are all secondary in nature and rely on figures published by a government agency, the USDA. Publications from this agency which contain the specific data series used are indicated by bibliographic reference numbers (32) through (38). Table 4.1 shows the detail of data sources.

Expected yields appearing as independent variables in the model are not observable. Those variables have to be estimated. In this study, it is assumed that farmers' yield expectations depend on the actual yields of the

Table 4.1. Data sources

Data	Sources
Actual acreage planted of all crops	USDA (34) and USDA (38)
March intention acreage of all crops	USDA (38)
Market prices or prices received by farmers for all crops	USDA (33)
U.S. average weighted loan rates for feed grains	USDA (32)[a]
U.S. average weighted loan rates for wheat and cotton	USDA (32)
U.S. price support rate for soybeans	USDA (32)
U.S. diversion payment rates for corn and sorghum	USDA (32)[a]
U.S. diversion payment rates for wheat	USDA (32)
Yield per acre	USDA (35), USDA (36), USDA (37)

[a]For 1952-1972 only, the rest were calculated in the same manner.

particular crop in past years. From this notion, three formulations of expected yields functions are utilized. They are the five-year moving average regression model, the time-trend regression model and the mixed model of two-year lagged actual yields and a time trend. The three of them are expressed as follows:

$$YE_{it} = a_{11}Y_{i(t-1)} + a_{12}Y_{i(t-2)} + a_{13}Y_{i(t-3)} + a_{14}Y_{i(t-4)} + a_{15}Y_{i(t-5)} \quad (4.1)$$

$$YE_{it} = a_{21} + a_{22}t + a_{23}t^2 \quad (4.2)$$

$$YE_{it} = a_{31} + a_{32}Y_{i(t-1)} + a_{33}Y_{i(t-2)} + a_{34}t + a_{35}t^2 \quad (4.3)$$

where

YE_i = expected yields of crop i,

Y_i = actual yields of crop i,

t = time-trend.

The estimates of the two equations above were obtained by O.L.S. from the actual data in the sample period. The estimated equations and the estimated expected yields are presented in Appendix A.

C. Empirical Models

This section contains the various equations that were fitted in this study. Four single-equation models for each of six U.S. crops will be presented. The nature of the models is specified in the following descriptions.

Model I: The explanatory variables in Model for each of six U.S. crops are expected prices and some policy variables of own crop and competitive crops, expected yields of own crop and competitive crops, a considered dummy variable and/or time trend. This model is from the general form of (2.42) and could be called a basic model.

Model II: The explanatory variables in Model II are the variables contained in Model I and the subjective variables of intended acreages of own crop and competitive crops. This is the model of the general form of (2.43) and could be called a revised model or model with subjective variables.

Model III: This model is the reduced model of Model II. With the dropping of the subjective variables of competitive crops from Model II, this model contains all the objective variables of Model I and the subjective variable of only the own crop. It was built for testing the significance of inter-commodity subjective variables.

Model IV: The explanatory variable in this model is only the own subjective variable of the crop concerned and was built to test for the significance of the coefficients of all objective variables.

The dependent variables in all models are the planted acreages in the commodities concerned. The details of the four models of six crops follow.

<u>Corn</u>:

The empirical models for corn presented here are based upon Houck and Ryan (10), Modigliani and Cohen (20), Ryan and Abel (27), USDA (32). The crops considered to be competitive with corn are sorghum and soybeans. Four models of corn supply response were constructed:

$$\begin{aligned} APCN_t = a_0 &+ a_4 PICN_t + a_5 DPCN_t + a_6 PSB_{t-1} + a_7 PSSB_t \\ &+ a_8 PIGM_t + a_9 YECN_t + a_{10} YEGM_t + a_{11} YESB_t \\ &+ a_{12} DVSIX + a_{13} T52 + e_{1t} \qquad \text{MODEL I} \qquad (4.4a) \end{aligned}$$

$$\begin{aligned} APCN_t = a_0 &+ a_1 AICN_t + a_2 AISB_t + a_3 AIGM_t + a_4 PICN_t \\ &+ a_5 DPCN_t + a_6 PSB_{t-1} + a_7 PSSB_t + a_8 PIGM_t \\ &+ a_9 YECN_t + a_{10} YEGM_t + a_{11} YESB_t + a_{12} DVSIX \\ &+ a_{13} T52 + e_{2t} \qquad \text{MODEL II} \qquad (4.4b) \end{aligned}$$

$$\begin{aligned} APCN_t = a_0 &+ a_1 AICN_t + a_4 PICN_t + a_5 DPCN_t + a_6 PSB_{t-1} \\ &+ a_7 PSSB_t + a_8 PIGM_t \div a_9 YECN_t + a_{10} YEGM_t \\ &+ a_{11} YESB_t + a_{12} DVSIX + a_{13} T52 + e_{3t} \qquad \text{MODEL III} \qquad (4.5) \end{aligned}$$

$$APCN_t = a_0 + a_1 AICN_t + e_{4t} \qquad \text{MODEL IV} \qquad (4.6)$$

Soybeans:

Based upon theoretical analysis and previous studies, soybean supply response models will be presented here. The crop considered to be competitive with soybeans is corn. Four models of soybean supply response were constructed as follows:

$$APSB_t = b_0 + b_3PSB_{t-1} + b_4PSSB_t + b_5PICN_t + b_6APSB_{t-1} + b_7YESB_t + b_8YECN_t + e_{1t} \quad \text{MODEL I} \quad (4.7)$$

$$APSB_t = b_0 + b_1AISB_t + b_2AICN_t + b_3PSB_{t-1} + b_4PSSB_t + b_5PICN_t + b_6APSB_{t-1} + b_7YESB_t + b_8YECN_t + e_{2t} \quad \text{MODEL II} \quad (4.8)$$

$$APSB_t = b_0 + b_1AISB_t + b_3PSB_{t-1} + b_4PSSB_t + b_5PICN_t + b_6APSB_{t-1} + b_7YESB_t + b_8YECN_t + e_{3t} \quad \text{MODEL III} \quad (4.9)$$

$$APSB_t = b_0 + b_1AISB_t + e_{4t} \quad \text{Model IV} \quad (4.10)$$

Sorghum:

Based upon theoretical analysis and previous studies, sorghum supply response models will be presented here. The crops considered to be competitive with sorghum are soybeans, corn, cotton, and wheat. Four models of sorghum supply response were constructed as follows:

$$\begin{aligned} APGM_t = c_0 &+ c_5 PFGM_t + c_6 DPGM_t + c_7 PSB_{t-1} + c_8 PSSB_t \\ &+ c_9 PFWT_t + c_{10} PWT_{t-1} + c_{11} PFCN_t + c_{12} PFCT_t \\ &+ c_{13} YEGM_t + c_{14} YESB_t + c_{15} YEWT_t + c_{16} YECN_t \\ &+ c_{17} YECT_t + c_{18} DVSIX + e_{1t} \qquad \text{MODEL I (4.11)} \end{aligned}$$

$$\begin{aligned} APGM_t = c_0 &+ c_1 AIGM_t + c_2 AISB_t + c_3 AICN_t + c_4 AIWT_t \\ &+ c_5 PFGM_t + c_6 DPGM_t + c_7 PSB_{t-1} + c_8 PSSB_t \\ &+ c_9 PFWT_t + c_{10} PWT_{t-1} + c_{11} PFCN_t + c_{12} PFCT_t \\ &+ c_{13} YEGM_t + c_{14} YESB_t + c_{15} YEWT_t + c_{16} YECN_t \\ &+ c_{17} YECT_t + c_{18} DVSIX + e_{2t} \qquad \text{MODEL II (4.12)} \end{aligned}$$

$$\begin{aligned} APGM_t = c_0 &+ c_1 AIGM_t + c_5 PFGM_t + c_6 DPGM_t + c_7 PSB_{t-1} \\ &+ c_8 PSSB_t + c_9 PFWT_t + c_{10} PWT_{t-1} + c_{11} PFCN_t \\ &+ c_{12} PFCT_t + c_{13} YEGM_t + c_{14} YEST_t + c_{15} YEWT_t \\ &+ c_{16} YECN_t + c_{17} YECT_t + c_{18} DVSIX + e_{3t} \end{aligned}$$

MODEL III (4.13)

$$APGM_t = c_0 + c_1 AIGM_t + e_{4t} \qquad \text{MODEL IV} \qquad (4.14)$$

Oats:

Oat supply response models will be presented here, based upon theoretical analysis and previous studies. The crops considered to be competitive with oats are barley and wheat. Four models of oat supply response were constructed as follows.

$$\begin{aligned} APOT_t = d_0 &+ d_4 PIOT_t + d_5 PIBY_t + d_6 PFWT_t + d_7 PWT_{t-1} \\ &+ d_8 YEOT_t + d_9 YEBY_t + d_{10} YEWT_t + d_{11} DVEIGH \\ &+ d_{12} T67 + d_{13} T67^2 + e_{1t} \qquad \text{MODEL I} \quad (4.15) \end{aligned}$$

$$\begin{aligned} APOT_t = d_0 &+ d_1 AIOT_t + d_2 AIBY_t + d_3 AIWT_t + d_4 PIOT_t \\ &+ d_5 PIBY_t + d_6 PFWT_t + d_7 PWT_{t-1} + d_8 YEOT_t \\ &+ d_9 YEBY_t + d_{10} YEWT_t + d_{11} DVEIGH + d_{12} T67 \\ &+ d_{13} T67^2 + e_{2t} \qquad \text{MODEL II} \quad (4.16) \end{aligned}$$

$$\begin{aligned} APOT_t = d_0 &+ d_1 AIOT_t + d_4 PIOT_t + d_5 PIBY_t + d_6 PFWT_t \\ &+ d_7 PWT_{t-1} + d_8 YEOT_t + d_9 YEBY_t + d_{10} YEWT_t \\ &+ d_{11} DVEIGH + d_{12} T67 + d_{13} T67^2 + e_{3t} \\ &\qquad \text{MODEL III} \quad (4.17) \end{aligned}$$

$$APOT_t = d_0 + d_1 AIOT_t + e_{4t} \qquad \text{MODEL IV} \quad (4.18)$$

Barley:

The crops considered to be competitive with barley are oats and wheat. The four models of barley supply response, based on theoretical analysis and previous studies as follows:

$$\begin{aligned}APBY_t = h_0 &+ h_4 PIBY_t + h_5 PIOT_t + h_6 PFWT_t + h_7 PWT_{t-1} \\ &+ h_8 YEBY_t + h_9 YEOT_t + h_{10} YEWT_t + h_{11} DVSIX \\ &+ h_{12} T52 + e_{1t} \qquad \text{MODEL I} \quad (4.19)\end{aligned}$$

$$\begin{aligned}APBY_t = h_0 &+ h_1 AIBY_t + h_2 AIOT_t + h_3 AIWT_t + h_4 PIBY_t \\ &+ h_5 PIOT_t + h_6 PFWT_t + h_7 PWT_{t-1} + h_8 YEBY_t \\ &+ h_9 YEOT_t + h_{10} YEWT_t + h_{11} DVSIX \\ &+ h_{12} T52 + e_{2t} \qquad \text{MODEL II} \quad (4.20)\end{aligned}$$

$$\begin{aligned}APBY_t = h_0 &+ h_1 AIBY_t + h_4 PIBY_t + h_5 PIOT_t + h_6 PFWT \\ &+ h_7 PWT_{t-1} + h_8 YEBY_t + h_9 YEOT_t + h_{10} YEWT_t \\ &+ h_{11} DVSIX + h_{12} T52 + e_{3t} \qquad \text{MODEL III} \quad (4.21)\end{aligned}$$

$$APBY_t = h_0 + h_1 AIBY_t + e_{4t} \qquad \text{MODEL IV} \quad (4.22)$$

Wheat:

Based upon theoretical analysis and previous studies, wheat supply response models will be presented here. The crops considered to be competitive with wheat are oats and barley. Four models of wheat supply response were constructed as follows:

$$APWT_t = m_0 + m_4PFWT_t + m_5DPWT_t + m_6PWT_{t-1} + m_7PIOT_t + m_8PIBY_t + m_9YEWT_t + m_{10}YEOT_t + m_{11}YEBY_t + e_{1t} \quad \text{MODEL I} \qquad (4.23)$$

$$APWT_t = m_0 + m_1AIWT_t + m_2AIOT_t + m_3AIBY_t + m_4PFWT_t + m_5DPWT_t + m_6PWT_{t-1} + m_7PIOT_t + m_8PIBY_t + m_9YEWT_t + m_{10}YEOT_t + m_{11}YEBY_t + e_{2t} \quad \text{MODEL II} \qquad (4.24)$$

$$APWT_t = m_0 + m_1AIWT_t + m_4PFWT_t + m_5DPWT + m_6PWT_{t-1} + m_7PIOT_t + m_8PIBY_t + m_9YEWT_t + m_{10}YEOT_t + m_{11}YEBY_t + e_{3t} \quad \text{MODEL III} \qquad (4.25)$$

$$APWT_t = m_0 + m_1AIWT_t + e_{4t} \quad \text{MODEL IV} \qquad (4.26)$$

D. Estimation Procedure and Methods of Analysis

Four single-equation models of the six U.S. crops presented were estimated by O.L.S. procedure in the primary study. The results of models of low and nonsignificant DW statistics will be presented in the study. Secondly, the models which showed rather high and significant DW statistics were reestimated by G.L.S. adjusted for autocorrelation errors. The first, second and third-order autocorrelation regressions were used. For each crop studied, when second-order autocorrelation coefficients are significant in some models, all models of that crop will be estimated by second-order autocorrelation regression. The same procedure will be conducted for using third-order autocorrelation regression in some crops. These estimations will provide the grounds for comparing the models for each crop.

Consider the following two models:

$$Y = B_1X_1 + U_1 \qquad \text{Model I} \qquad (4.27)$$

$$Y = B_1X_1 + B_2X_2 + U_2 \qquad \text{Model II} \qquad (4.28)$$

where

Y = nxl matrix of dependent variable,

X_1 = nxk matrix of h explanatory variables,

X_2 = nx(k-h) matrix of (k-h) explanatory variables,

U_1 = nxl matrix of error term,

U_2 = nxl matrix of error term.

To test the null hypothesis:

$$H_0: \; B_2 = 0, \tag{4.29}$$

suppose that the O.L.S. is applied to these models. Suppose that the DW statistic of Model II is high and significant. Then, G.L.S. adjusted for autocorrelated errors must be used to estimate the equation of Model II. Model II will become

$$Y = B_1X_1 + B_2X_2 + \rho_2U_{2,t-1} + e_2 \tag{4.30}$$

If $B_2 = 0$ is to be tested, the version of Model I which is to be compared with this model will be

$$Y = B_1X_1 + \rho_1U_{1,t-1} + e_1 \tag{4.31}$$

The G.L.S. adjusted for autocorrelation in errors must be applied to Model I of (4.27) in order to get the results from two models and to compute the F-ratio for testing H_0: $B_2 = 0$.

The F-ratio formula for testing the significance of B_2 have been presented in Section III.A.2.

Three soybean supply response models, which contained a lagged independent variable as an explanatory variable, were estimated by using instrumental variables. The methods can be summarized as follows:

a) Regress $APSB_{t-1}$ on all explanatory variables contained in the model and their values lagged one year,

b) calculate the estimated value of $APSB_{t-1}$, $\hat{APSB}_{t-1}$, from a,

c) regress $APSB_t$ on $\hat{APSB}_{t-1}$ and other variables by first, second and third autocorrelation regression and selecting the most appropriate one by using the same criteria as mentioned at the beginning of this section

The variables of $\hat{APSB}_{t-1}$ are called instrumental variables. The details of this method are in Fuller (7).

The next analysis, which is the main purpose of this study, is to compare the performance of the models studied. F-ratios of many pairs of models will be calculated to test the significance of the coefficients of certain variables involved. The details of this calculation were discussed in Chapter III, Section A.2.

From the testing above, the superior models of each crop were selected. Then, a set of six equations was reestimated by seemingly unrelated regression.

To verify which model for each crop would give better performance in estimating the estimated value of acreage planted, turning point analyses were used in the final part of the analyses.

V. EMPIRICAL RESULTS

The purpose of this chapter is to present the empirical results of the study. The chapter is divided into four sections: the estimated crop supply response equations; the comparison of the models; the seemingly unrelated regression of the system of superior models and the turning point analyses.

A. The Estimated Crop Supply Response Equations

Four estimated equations of each of the six crops will be presented in Tables 5.1 through 5.6. The first line for each variable presents the estimated coefficients corresponding to the models indicated at the top of the columns. The values in parentheses are the ratios of the coefficients to their standard errors, or t-ratios. R^2 is the multiple coefficient of determination; F is the overall F-ratio; s is the standard error of estimate. DW is the Durbin-Watson statistic which is presented when the O.L.S. procedure is used. For the models which are estimated by an autocorrelation regression procedure, r_1, r_2, and r_3 stand for the coefficients of first, second, and third-order autocorrelation respectively.

Table 5.1. O.L.S. estimates, U.S. corn planted acreage response, 1952-1974 (dependent variable = $APCN_t$)

Variables and Statistics	Model I	Model II	Model III	Model IV
Constant	-39,558.33 (-0.84)	-16,542.47 (-0.24)	-44,586.33 (-0.94)	9,469.70 (1.18)
$AICN_t$		0.1845 (0.97)	0.17 (1.04)	0.85*** (7.87)
$AISB_t$		-0.6744 (-0.96)		
$AIGM_t$		-0.0134 (-0.03)		
$PICN_t$	14,549.76*** (3.34)	7,805.88 (0.95)	11,235.69* (2.09)	
$DPCN_t$	1,947.20 (0.18)	-8,339.85 (-0.57)	837.87 (0.08)	
PSB_{t-1}	4,175.24 (0.98)	5,417.02 (1.10)	4,548.07 (1.07)	
$PSSB_t$	-15,824.21*** (-3.58)	-12,663.41** (-2.34)	-13,903.44*** (-2.92)	
$PIGM_t$	-6,785.09* (-2.01)	-4,911.40 (-0.98)	-6,281.36* (-1.85)	

*Significant at .10 level.

**Significant at .05 level.

***Significant at .01 level.

Table 5.1 (Continued)

Variables and Statistics	Model I	Model II	Model III	Model IV
$YECN_t$	-28.86 (-0.24)	113.92 (0.68)	24.52 (0.19)	
$YESB_t$	7,748.10** (2.78)	5,786.56 (1.57)	7,136.94** (2.52)	
$YEGM_t$	-506.98** (-2.64)	-564.44** (-2.76)	-547.18** (-2.81)	
DVSIX	14,992.92** (4.56)	14,625.74*** (3.74)	13,840.22*** (4.00)	
T_{52}	-3,204.03** (-2.89)	-1,459.61 (-0.78)	-2,897.99** (-2.53)	
F	33.081***	23.665***	30.376***	62.050***
R^2	0.9650	0.9716	0.9681	0.7471
s	1725.64	1795.52	1719.8	3505.9
D.W.	1.917	1.995	1.886	1.33

1. Corn

Four models of corn supply response were estimated by the O.L.S. procedure. Model I, which contains all objective variables, seems to be a good fit. R^2 is rather high (0.9650) and the overall F-ratio is 33.081 which is significant at a 1 percent level. Most of the coefficients of the variables contained in Model I are highly significant. Adding three intended acreages of corn and two competitive crops (soybeans and sorghum) to Model I reduced the level of significance of the other variables. The coefficients of $DPCN_t$, PSB_{t-1} and $YECN_t$ are nonsignificant at a 10 percent level in all three models containing them. The coefficients of $PSSB_t$, $YEGM_t$ and DVSIX are significant in the three models containing them.

The coefficient of $AICN_t$ is highly significant in Model IV which contains only one explanatory variable. When adding the other explanatory variables to obtain Model II and Model III, the coefficient of $AICN_t$ becomes nonsignificant. The details of the resulting parameter estimates are presented in Table 5.1.

2. Soybeans

Four models of soybean supply response were estimated by the second-order autocorrelation regression procedure. Model II and Model IV seem to be good fits. The R^2 of the two models has the same value at 0.9744. The overall F-ratios of both models are very high and significant. R^2 in Model I is rather high at 0.9745. Adding two intended acreages of soybeans and corn ($AISB_t$ and $AICN_t$) to Model I tended to reduce the level of significance of the other variables. The coefficient of $AISB_t$ is highly significant in all three models containing it. The coefficients of $PSSB_t$, $PICN_t$, $A\hat{P}SB_{t-1}$ and $YESB_t$ are nonsignificant at a 10 percent level in the three models that contain them. The details of the resulting parameter estimates of soybean supply response are presented in Table 5.2.

3. <u>Sorghum</u>

Four models of sorghum supply response were estimated by the second-order autocorrelation regression procedure. All models seem to be a good fit. All except Model IV have a high R^2. However, adding four subjective variables ($AIGM_t$, $AISB_t$, $AICN_t$ and $AIWT_t$) to Model I reduced the level of significance of the other variables. The coefficients of $PIGM_t$, PSB_{t-1}, $PSSB_t$, $PFWT_t$, PWT_{t-1}, $PICN_t$, $PFCT_t$, $YEGM_t$ and $YECN_t$ are nonsignificant at a 10 percent level in all three models. The details of resulting parameter estimates are presented in Table 5.3.

Table 5.2. G.L.S. adjusted for autocorrelation, U.S. soybean planted acreage response, 1952-1974 (dependent variable = $APSB_t$)

Variables and Statistics	Model I	Model II	Model III	Model IV
Constant	-14,389.221 (-0.73)	-5,507.446 (-0.58)	329.5266 (0.04)	279.9632 (0.74)
$AISB_t$		0.87332*** (3.75)	0.9965*** (4.16)	0.9948*** (89.03)
$AICN_t$		0.12942 (1.64)		
PSB_{t-1}	5,729.274** (2.65)	2,462.153 (1.69)	1271.804 (0.95)	
$PSSB_t$	-186.297 (-0.07)	-197.2888 (-0.12)	-473.4144 (-0.29)	
$PICN_t$	-6,105.841 (-1.68)	-4,093.283 (-1.46)	-925.538 (-0.43)	
$\hat{APSB}_{t-1}$	0.22734 (1.08)	-0.058416 (-0.31)	-0.1957 (-0.98)	
$YESB_t$	418.639 (0.45)	-377.2739 (-0.86)	-117.193 (-0.27)	
$YECN_t$	334.706*** (2.97)	145.4029 (1.60)	116.202 (1.34)	

** Significant at .05 level.

*** Significant at .01 level.

Table 5.2 (Continued)

Variables and Statistics	Model I	Model II	Model III	Model IV
F	95.36***	634.78***	540.15***	7925.43***
R^2	0.9745	0.9974	0.9963	0.9974
s	1847.09	1054.99	1111.36	979.9
r_1	-0.2134 (-1.00)	0.3265* (1.56)	0.249 (1.17)	0.3021* (1.609)
r_2	0.0258 (0.121)	0.196 (0.94)	0.106 (0.50)	0.4358*** (2.322)

*Significant at .10 level.

4. Oats

Four models of oat supply response were estimated by the third-order autocorrelation regression procedure. Model I seems to be a good fit. At the level of 0.9970, the R^2 is very high. The coefficients of seven variables are significant at a 5 percent level. Adding three subjective variables ($AIOT_t$, $AIBY_t$ and $AIWT_t$) to Model I reduced the level of significance of the other variables. The coefficients of $AIOT_t$, PWT_{t-1}, T67 are significant in all models.

Table 5.3. G.L.S. adjusted for autocorrelation, U.S. sorghum planted acreage response, 1952-1974 (dependent variable = $APGM_t$)

Variables and Statistics	Model I	Model II	Model III	Model IV
Constant	104,600.17 (3.82)	58,093.53 (1.22)	108,771.00 (2.76)	1,450.73 (0.87)
$AIGM_t$		0.626 (1.36)	-0.041 (-0.13)	0.9014*** (10.32)
$AISB_t$		0.411 (0.73)		
$AICN_t$		-0.222 (-1.13)		
$AIWT_t$		-1.48 (-1.68)		
$PIGM_t$	-62.82 (-0.023)	-2038.12 (-0.50)	169.90 (0.04)	
$DPGM_t$	-25,294.37** (-2.54)	-5,796.22 (-0.32)	-26,387.46* (-2.08)	
PSB_{t-1}	-3,697.99 (-1.24)	-2,329.18 (-0.53)	-3,956.42 (-0.99)	
$PSSB_t$	1,068.03 (0.199)	-1,875.82 (-0.27)	902.19 (0.156)	
$PFWT_t$	-2.986.44 (-1.17)	4,277.03 (0.83)	-2,884.12 (-1.01)	

*Significant at .10 level.

**Significant at .05 level.

***Significant at .01 level.

Table 5.3 (Continued)

Variables and Statistics	Model I	Model II	Model III	Model IV
PWT_{t-1}	744.39 (0.44)	-1,137.18 (-0.50)	733.51 (0.39)	
$PICN_t$	-5,450.09 (-1.29)	14,412.23 (1.28)	-5,665.43 (-1.14)	
$PFCT_t$	-16,591.03 (-1.276)	-30,662.50 (-1.69)	-16,744.98 (-1.16)	
$YEGM_t$	121.44 (0.54)	124.04 (0.52)	128.52 (0.53)	
$YESB_t$	-5,261.28** (-2.37)	1,628.76 (0.36)	-5,563.96 (-1.78)	
$YEWT_t$	7,079.28** (2.80)	-830.03 (-0.16)	7,310.69** (2.32)	
$YECN_t$	-266.34 (-1.56)	-281.81 (-1.48)	-264.13 (-1.42)	
$YECT_t$	-226.16* (-2.13)	-69.65 (-0.44)	-229.19* (-1.95)	
DVSIX	-2,659.77 (-0.75)	-72.59 (-0.02)	-2,784.63 (-0.73)	
F	28.69***	16.22***	20.18***	106.47***
R^2	0.9805	0.9865	0.9774	0.8353
s	1076.81	1171.96	1197.41	1543.06
r_1	0.598*** (2.98)	0.439** (2.19)	0.541*** (2.68)	0.246 (1.19)
r_2	0.268* (1.33)	0.274* (1.36)	0.251 (1.25)	0.119 (0.57)

The coefficient of $PFOT_t$ is nonsignificant in all models. The details of the parameter estimates of oat supply response are presented in Table 5.4.

5. Barley

Four models of barley supply response were estimated by the third-order autocorrelation regression procedure. Model II and Model III seem to be better than the other two. Adding three subjective variables ($AIBY_t$, $AIOT_t$ and $AIWT_t$) to Model I did not have much effect on the level of significance of the other variables. However, adding those three variables results in a higher R^2, and the coefficients of all three added variables are significant. The coefficients of $AIBY_t$ and $PIBY_t$ are highly significant in all models that contained them. The coefficients of $YEBY_t$, $YEOT_t$, $YEWT_t$ and T52 are nonsignificant at a 10 percent level in all three. The details of the parameter estimates of barley supply response are presented in Table 5.5.

6. Wheat

Four models of wheat supply response were estimated by the second-order autocorrelation regression procedure. Model I seems to be a good fit. Its R^2 is rather high at 0.9220. However, adding three subjective variables ($AIWT_t$, $AIOT_t$ and $AIBY_t$) increased the level of significance of other variables. Furthermore, the coefficients of all subjective

Table 5.4. G.L.S. adjusted for autocorrelation, U.S. oat planted acreage response, 1952-1974 (dependent variable = $APOT_t$)

Variables and Statistics	Model I	Model II	Model III	Model IV
Constant	87,819.59 (5.62)	51,218.33 (5.03)	40,644.51 (3.05)	-59.4877 (-0.08)
$AIOT_t$		0.66*** (6.31)	0.664*** (4.98)	0.97454*** (43.71)
$AIBY_t$		0.17 (0.79)		
$AIWT_t$		-0.45** (-2.60)		
$PIOT_t$	4,456.82 (0.78)	3,608.50 (1.28)	4,561.50 (1.46)	
$PIBY_t$	5,411.04* (2.05)	3,938.22** (2.53)	1,747.29 (1.14)	
$PFWT_t$	-13,137.37*** (-4.53)	-2,440.37 (-1.22)	-5,944.55** (-2.53)	
PWT_{t-1}	-4,522.98* (-1.87)	-2,102.13* (-1.82)	-2,189.72* (-2.11)	
$YEOT_t$	-736.81*** (-4.39)	-147.99 (-1.51)	-252.71* (-2.03)	
$YEBY_t$	1,009.47*** (4.42)	91.62 (0.51)	232.63 (1.14)	
$YEWT_t$	-871.05 (-1.13)	-1,297.89*** (-3.15)	-519.86 (-1.20)	
DVEIGH	-23,816.10** (-2.65)	4,167.27 (0.67)	-5,013.72 (-0.84)	

*Significant at .10 level.

**Significant at .05 level.

***Significant at .01 level.

Table 5.4 (Continued)

Variables and Statistics	Model I	Model II	Model III	Model IV
T67	-2,071.35*** (-3.93)	-603.04* (-1.99)	-997.65** (-2.81)	
$T67^2$	23.44 (0.92)	44.74** (3.13)	34.68** (2.60)	
F	403.65***	1,029.64***	1,400.71***	1,910.25***
R^2	0.9970	0.9993	0.9993	0.9891
s	1139.99	520.47	634.89	883.70
r_1	0.121 (0.642)	0.314* (1.566)	0.283* (1.639)	-0.232 (-1.19)
r_2	0.254* (1.387)	-0.169 (-0.810)	0.129 (0.718)	-0.205 (-1.04)
r_3	0.426** (2.259)	0.269* (1.341)	0.562*** (3.257)	0.354** (1.81)

variables themselves are highly significant at a 1 percent level. The coefficients of $AIWT_t$ in three models are strongly significant at a 1 percent level. The coefficients of $DPWT_t$, PWT_{t-1} and $YEOT_t$ are nonsignificant in all three models. The details of the resulting parameter estimates of wheat supply response are presented in Table 5.6.

Table 5.5. G.L.S. adjusted for autocorrelation, U.S. barley planted acreage response, 1952-1974 (dependent variable = $APBY_t$)

Variables and Statistics	Model I	Model II	Model III	Model IV
Constant	7,594.07 (0.31)	1,929.05 (0.27)	-2,309.34 (-0.36)	-405.358 (-0.610)
$AIBY_t$		0.972*** (17.66)	1.51*** (13.70)	1.01907*** (19.731)
$AIOT_t$		0.052* (1.81)		
$AIWT_t$		-0.227*** (-3.23)		
$PIBY_t$	4,450.37* (1.86)	2,529.11*** (5.22)	1,830.70** (2.67)	
$PIOT_t$	-9,583.11* (-1.76)	295.89 (0.27)	1,507.89 (0.88)	
$PFWT_t$	-8,127.00*** (-3.86)	508.77 (0.94)	-136.51 (-0.16)	
PWT_{t-1}	2,678.35 (1.15)	-943.57** (-2.34)	-1,444.40** (-2.21)	
$YEBY_t$	301.176 (0.92)	-15.02 (-0.31)	69.8056 (0.77)	
$YEOT_t$	114.3447 (0.71)	24.63 (0.92)	-30.217 (-0.68)	

*Significant at .10 level.

**Significant at .05 level.

***Significant at .01 level.

Table 5.5 (Continued)

Variables and Statistics	Model I	Model II	Model III	Model IV
$YEWT_t$	326.0162 (0.38)	-125.48 (-0.50)	-11.391 (-0.05)	
DVSIX	1,566.435 (0.917)	467.175* (1.83)	554.64 (1.15)	
T_{52}	-813.208 (-1.198)	56.175 (0.43)	-60.348 (-0.32)	
F	16.77***	1,859.84***	291.90***	389.29***
R^2	0.9207	0.9996	0.9959	0.9488
s	1127.41	161.64	314.45	435.23
r_1	0.049 (0.235)	0.509*** (2.816)	0.124 (0.644)	-0.398** (-1.192)
r_2	0.210 (1.032)	0.307* (1.536)	0.075 (0.387)	-0.144 (-0.65)
r_3	-0.10 (-0.194)	0.498*** (2.754)	0.390** (2.029)	0.111 (0.53)

Table 5.6. G.L.S. adjusted for autocorrelation, U.S. wheat planted acreage response, 1952-1974 (dependent variable = $APWT_t$)

Variables and Statistics	Model I	Model II	Model III	Model IV
Constant	6,338.82 (0.92)	-13,360.35 (-1.91)	-2,286.18 (-0.64)	412.57 (0.82)
$AIWT_t$		1.136*** (8.19)	1.297*** (7.05)	0.972*** (26.89)
$AIOT_t$		0.242*** (5.00)		
$AIBY_t$		-0.458*** (-4.08)		
$PFWT_t$	4,878.40* (1.83)	-658.75 (-0.62)	-1,084.615 (-0.71)	
$DPWT_t$	-621.92 (-0.54)	68.13 (0.22)	1,065.87 (1.62)	
PWT_{t-1}	187.87 (0.06)	821.32 (0.82)	-626.25 (-0.46)	
$PIOT_t$	-1,946.84 (-0.30)	-4,932.29** (-2.21)	-308.95 (-0.10)	
$PIBY_t$	5,283.79** (2.40)	-360.06 (-0.38)	-952.49 (-0.65)	
$YEWT_t$	-398.98 (-0.93)	843.34** (2.64)	200.45 (0.96)	
$YEOT_t$	136.29 (0.77)	-3.61 (-0.06)	-70.55 (-0.73)	
$YEBY_t$	13.15 (0.06)	-234.32** (-2.25)	-3.645 (-0.03)	

*Significant at .10 level.

**Significant at .05 level.

***Significant at .01 level.

Table 5.6 (Continued)

Variables and Statistics	Model I	Model II	Model III	Model IV
F	20.68***	424.72***	66.72***	723.19***
R^2	0.9220	0.9977	0.9788	0.9718
s	1351.57	348.65	660.5	637.4
r_1	0.258 (1.27)	0.750*** (4.06)	0.051 (0.25)	0.222 (1.072)
r_2	0.232 (1.15)	0.462** (2.50)	0.252 (1.25)	0.135 (0.651)

It may be noted that there are many explanatory variables in the crop supply response models, especially in the sorghum supply responses. The more explanatory variables there are, the smaller the number of degrees of freedom. To conserve the degrees of freedom, two methods of data transformation were employed. The first method of transformation was to multiply the expected prices by expected yields of corresponding crops in each model. The second method was to derive price ratios and expected yield ratios. The price ratio was set up as follows:

$$\frac{\text{expected price of own crop}}{\text{expected price of competing crop}} .$$

The expected yield ratio was set up in a similar manner.

Regression analysis of the transformed data did not provide better results. Some are inferior to the results of regression with ordinary data. Therefore, the results of transformed data are not presented.

B. Comparison of the Models

As mentioned previously, the main objective of this study is to test the hypothesis that a better explanation of planted acreage can be obtained from a combination of subjective data and objective data than can be obtained from use of either type of data alone. This hypothesis is equivalent to stating that either Model II or Model III of each crop is the best. In order to conclude whether or not these models are superior, five null hypotheses and the F-ratios are used. The null hypotheses and F-ratios are as follows:

H_o: 1 - Model II is not superior to Model I,

H_o: 2 - Model II is not superior to Model III,

H_o: 3 - Model II is not superior to Model IV,

H_o: 4 - Model III is not superior to Model IV,

H_o: 5 - Model III is not superior to Model I,

$$F_{n_1-n_2,n_2} = \frac{(R^2_{\text{full model}} - R^2_{\text{reduced model}})/n_1-n_2}{(1-R^2_{\text{full model}})/n_2} \quad (5.1)$$

where

n_1 = degrees of freedom of reduced model,

n_2 = degrees of freedom of full model.

The other objective of the study is to test the hypothesis that adding the subjective data on the competing crops in the planted acreage responses results in a better explanation. In this study, the intended acreages of the competing crops were added into the model, as Model II, of each of six crops. In order to meet this objective, only hypothesis 2 will be used.

The results of testing and calculation of F-ratios are presented for corn supply responses in detail below. Comparing the two results of regression analysis of Model II and Model I is equivalent to testing the null hypothesis H_o: 1 that $a_1 = a_2 = a_3 = 0$, or Model II is not superior to Model I. This procedure will test whether adding the subjective variables into the basic model improves the explanation of the corn supply response equation.

$$F_{(3,10)} = \frac{(R_f^2-R_r^2)/13-10}{(1-R_f^2)/23-13} = \frac{(0.9716 - 0.9650)/3}{(1 - 0.9716)/10} = 0.77 \quad (5.2)$$

where

R_f^2 = coefficient of multiple determination for the full model (Model II),

R_r^2 = coefficient of multiple determination for the reduced model (Model I).

The above F-ratio is nonsignificant,[1] which implies that the null hypothesis, that coefficients of three subjective variables are equal to zero, fails to be rejected. Therefore, we have evidence that Model II is not superior to Model I.

The remaining four hypotheses are tested in the same way.

H_o: 2 - Model II is not superior to Model III.

$$F_{(2,10)} = \frac{(0.9716 - 0.9681)/13-11}{(1 - 0.9716)/23-13} = 0.62 \qquad (5.3)$$

This F-ratio is nonsignificant. Therefore, we have evidence that Model II is not superior to Model III.

H_o: 3 - Model II is not superior to Model IV.

$$F_{(12,10)} = \frac{(0.9716 - 0.7471)/13-1}{(1 - 0.9716)/23-13} = 6.59 \qquad (5.4)$$

This F-ratio is significant and H_o: 3 is rejected. Therefore, there is evidence that model II of corn is superior to Model IV.

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[1]Throughout this section, .05 level of significance is used.

H_o: 4 - Model III is not superior to Model IV.

$$F_{(10,12)} = \frac{(0.9681 - 0.7471)/11-1}{(1 - 0.9681)/23-11} = 8.31 \qquad (5.5)$$

This F ratio is significant and we reject the H_o: 4. Therefore, we have evidence that Model III is superior to Model IV.

H_o: 5 - Model III is not superior to Model I.

$$F_{(1,12)} = \frac{(0.9681 - 0.9650)/11-10}{(1 - 0.9681)/23-11} = 1.17 \qquad (5.6)$$

This F-ratio is nonsignificant and we fail to reject the null hypothesis. Therefore, evidence exists that Model III is not superior to Model I.

From the above analyses, it can be concluded that Model I of the corn supply response is superior. Adding subjective variables in building corn supply response model did not result in any improvement.

The F-ratios for testing the above five null hypotheses for all six U.S. crops are shown in Table 5.7. The interpretations of the test results are in Table 5.8.

In Table 5.8, "$\not>$" means "not superior to"; "A" denotes the acceptance of the null hypothesis; "R" denotes the rejection of the null hypothesis. For example, in testing H_o: 1 of soybean supply response, the null hypothesis is rejected from which it can be concluded that Model II is superior to Model I. The rest of the tests can

Table 5.7. F-ratios for comparison of the models

	Corn	Soybeans	Sorghum	Oats	Barley	Wheat
H_o: 1 Model II vs. Model I	0.77	66.18***	0.56	10.96***	730.56***	131.42***
H_o: 2 Model II vs. Model III	0.62	6.36**	1.12	0.00	51.39***	49.22***
H_o: 3 Model II vs. Model IV	6.59***	0.00	3.29	14.53***	128.28***	78.48***
H_o: 4 Model III vs. Model IV	8.31***	0.00	3.59**	17.59***	16.61***	0.58
H_o: 5 Model III vs. Model I	1.17	94.37***	0.00	39.66***	238.73***	37.52***

**Significant at .05 level.

***Significant at .01 level.

Table 5.8. Interpretation of F-ratios in Table 5.7

Null Hypothesis[a]	Corn	Soybeans	Sorghum	Oats	Barley	Wheat
H_o: 1 II $\not>$ I	A[b]	R	A	R	R	R
H_o: 2 II $\not>$ III	A	R	A	A	R	R
H_o: 3 II $\not>$ IV	R	A	A	R	R	R
H_o: 4 III $\not>$ IV	R	A	R	R	R	A
H_o: 5 III $\not>$ I	A	R	A	R	R	R

[a] $\not>$ means "not superior to".

[b] .05 level of significance is used, A means "accept the null hypothesis", R means "reject the null hypothesis".

be interpreted in the same manner.

The results of the other five crop supply responses are summarized as follows:

1. Comparison of soybean supply response models:
    a. Model II is superior to Model I,
    b. Model II is superior to Model III,
    c. Model II is not superior to Model IV,
    d. Model III is not superior to Model IV,
    e. Model III is superior to Model I.

From the above, it can be concluded that Model II and Model IV are superior to the others.

2. Comparison of sorghum supply response models:
    a. Model II is not superior to Model I,
    b. Model II is not superior to Model III,
    c. Model II is not superior to Model IV,
    d. Model III is superior to Model IV,
    e. Model III is not superior to Model I.

Given the above results, it can be concluded that Model I of the sorghum supply response is superior. The incorporation of subjective variables into the model did not improve it.

3. Comparison of oat supply response models:
    a. Model II is superior to Model I,
    b. Model II is not superior to Model III,

c. Model II is superior to Model IV,

d. Model III is superior to Model IV,

e. Model III is superior to Model I.

From the above results, it can be concluded that Model III of the oat supply response is superior. Incorporating only oat intended acreage yields improvement in estimating oat planted acreage response. The intended acreages of competing crops do not significantly affect oat planted acreage.

4. Comparison of barley supply response models:

   a. Model II is superior to Model I,

   b. Model II is superior to Model III,

   c. Model II is superior to Model IV,

   d. Model III is superior to Model IV,

   e. Model III is superior to Model I.

Within the parameters of the sample studied, it can be concluded that Model II of the barley supply response is superior. The subjective variables of barley and the competitive crops affect the barley planted acreage.

5. Comparison of wheat supply response models:

   a. Model II is superior to Model I,

   b. Model II is superior to Model III,

   c. Model II is superior to Model IV,

   d. Model III is not superior to Model IV,

e. Model III is superior to Model I.

From the above results, it can be concluded that Model II of the wheat supply response is superior. The subjective variables of wheat and the competitive crops affect wheat planted acreage.

C. Seemingly Unrelated Regression

From the test of significance of comparing the models in Section B, a set of equations composed of Model I of corn, Model II of soybeans, Model I of sorghum, Model III of oats, Model II of barley and Model II of wheat was selected. The interpretations of the previous section determined the selection of selecting those models. For example, in the case of corn; Model I was selected because in the comparison of the models, the test results show that Model II is not superior to Model I and Model III, and Model III is not superior to Model I; then, without considering the other two tests, Model I is superior. In the case of soybeans the above results show that there is no significant reason to choose between Model II or Model IV. Model II was selected because it was built from the theoretical point of view, whereas Model IV was not. As mentioned earlier Model IV was built for providing a test for comparison. Therefore, Model IV could not be represented in a single supply response equation at this time.

The Seemingly Unrelated Regression proposed by Parks (24, pp. 503-504) was used to estimate the above set of equations. The Aitken estimators and residual correlation matrix are presented in Table 5.9 and Table 5.10 respectively.

The Seemingly Unrelated Regression (SUR) estimates provide some improvement for corn and soybean supply response. There are more significant coefficients than in the separate Least Square estimates. The coefficient of PSB_{t-1} in the corn supply response, which is nonsignificant in Ordinary Least Squares, is significant at a 10 percent level in this estimate. The coefficients of PSB_{t-1} and $YECN_t$ in the soybean supply response, which are nonsignificant in G.L.S., are significant at a 10 percent level here.

There is no explicit conclusion for the sorghum and barley supply responses. The coefficients of PWT_{t-1} and $PICN_t$ in the sorghum supply response, which are nonsignificant in G.L.S., are significant at a 10 percent level here. In contrast, the coefficient of $YECT_t$, which is significant in G.L.S., is nonsignificant in the SUR. Furthermore, the SUR estimates reduced the level of significance of the coefficients of $YESB_t$ and $YEWT_t$. The coefficients of $PFWT_t$ and $YEOT_t$ in the barley supply response, which are nonsignificant in G.L.S., are significant here, while the

Table 5.9. Seemingly unrelated estimates, U.S. crops Model, 1952-1974[a]

	Corn, I	Soybeans, II	Sorghum, I	Oats, III	Barley, II	Wheat, II
VARIABLES	Constant -36117.158 (-0.99)	Constant -2649.94 (-0.66)	Constant 52179.801 (1.73)	Constant 20191.81 (1.08)	Constant -16767.11 (-1.87)	Constant -12503.86 (-1.16)
	$PICN_t$ 14889.434*** (4.21)	$AISB_t$ 0.7945*** (3.81)	$PIGM_t$ 1149.52 (0.48)	$AIOT_t$ 0.68309*** (4.92)	$AIBY_t$ 1.0458*** (18.13)	$AIWT_t$ 1.138*** (7.11)
	$DPCN_t$ 3696.817 (0.44)	$AICN_t$ 0.0734 (1.66)	$DPGM_t$ -14828.446 (-1.56)	$PIOT_t$ 5358.106 (1.58)	$AIOT_t$ 0.0945*** (3.42)	$AIOT_t$ 0.2415*** (4.75)
	PSB_{t-1} 6419.704* (1.98)	PSB_{t-1} 2471.318 (1.80)	PSB_{t-1} -418.2907 (-0.16)	$PIBY_t$ 1612.684 (0.96)	$AIWT_t$ -0.1473** (-2.45)	$AIBY_t$ -0.4709** (-2.50)
	$PSSB_t$ -17205.71*** (-4.80)	$PSSB_t$ -848.687 (-0.57)	$PSSB_t$ -7511.985 (-1.24)	PFWT -4094.25* (-2.02)	$PIBY_t$ 2326.47*** (5.97)	$PFWT_t$ -813.098 (-0.57)
	$PIGM_t$ -7947.61** (-2.92)	$PICN_t$ -4068.61 (-1.55)	$PFWT_t$ 4247.03 (1.04)	PWT_{t-1} -1887.81 (-1.41)	$PIOT_t$ 897.118 (0.90)	$DPWT_t$ 107.425 (0.35)
	$YECN_t$ -233.59* (-2.04)	$A\widehat{PSB}_{t-1}$ 0.01475 (0.08)	PWT_{t-1} 5743.51* (1.92)	$YEOT_t$ -242.9426 (-1.75)	$PFWT_t$ 1471.37** (2.33)	PWT_{t-1} 677.933 (0.65)
	$YESB_t$ 7901.98*** (3.70)	$YESB_t$ -444.597 (-1.09)	$PICN_t$ -6877.52* (-1.98)	$YEBY_t$ 281.81 (1.19)	PWT_{t-1} -229.758 (-0.57)	$PIOT_t$ -5012.48 (-1.66)
	$YEGM_t$ -452.87** (-2.78)	$YECN_t$ 161.44* (1.97)	$PFCT_t$ -1551.92 (-0.13)	$YEWT_t$ 137.686 (0.16)	$YEBY_t$ 18.5789 (0.46)	$PIBY_t$ -217.900 (-0.18)
	DVSIX 15427.57*** (5.93)		$YEGM_t$ -140.59 (-0.71)	DVEIGH -11652.58 (-1.00)	$YEOT_t$ 43.3404* (1.93)	$YEWT_t$ 842.883** (2.29)

[a] t ratios shown in parentheses are only approximate.

*Significant at .10 level.

**Significant at .05 level.

***Significant at .01 level.

Table 5.9 (Continued)

	Corn, I	Soybeans, II	Sorghum, I	Oats, III	Barley, II	Wheat, II
VARIABLES	T52 -3003.34*** (-3.42)		$YESB_t$ -3820.16* (-2.11)	T67 -1148.96* (-1.98)	$YEWT_t$ 399.318 (1.42)	$YEOT_t$ -5.799 (-0.09)
			$YEWT_t$ 4280.22* (1.92)	$T67^2$ 21.4314 (1.46)	DVSIX 223.25 (0.99)	$YEBY_t$ -239.427** (-2.20)
			$YECN_t$ -137.94 (-0.98)		T52 -177.32 (-1.35)	
			$YECT_t$ -57.5137 (-0.53)			
			DVSIX 929.03 (0.29)			

Table 5.10. Residuals correlation matrix

	Corn Model I	Soybeans Model II	Sorghum Model I	Oats Model III	Barley Model II	Wheat Model II
Corn	1.000	0.30165	-0.25158	-0.53415	-0.15458	0.18370
Soybeans		1.000	0.32875	-0.02335	-0.29636	0.00120
Sorghum			1.0000	0.31017	-0.10116	-0.10457
Oats				1.0000	0.31061	0.07344
Barley					1.0000	0.03142
Wheat						1.0000

coefficient of PWT_{t-1}, which is significant in G.L.S., is nonsignificant.

There is no improvement in the significance level of coefficients for the oat and wheat supply responses. The coefficients of PWT_{t-1}, $YEOT_t$ and $T67^2$ in the oat supply response, which are significant in G.L.S., are nonsignificant here. The coefficient of $PIOT_t$ in wheat supply response, which is significant in G.L.S., is nonsignificant in the SUR.

However, the t-ratio for SUR estimates are only approximate and have limited value in testing hypothesis. The other statistics, i.e., overall F-ratio, R^2,s, are unavailable from the package program utilized; therefore, they are not presented here.

D. Model Validation: Chi Square Test of Predictions of Turning Points

Econometric models which are more accurate in estimating the real world are of more use to analysts and have the best potential for use by forecasters. In this section, the Chi Square test of the relationship between the estimated turning points and actual turning points of each crop will be used for model validation. The process of analysis was conducted by computing the estimated value of planted acreage of the selected models of each crop, and counting the turning points of actual planted acreage and estimated planted acreage. Then, the contingency tables were set up for computing chi square. The general form of the contingency table is presented in Table 5.11, where

n_{11} = number of turning points which actually occurred and were estimated,

n_{12} = number of turning points that actually did not occur but were estimated,

n_{21} = number of turning points which actually occurred but were not estimated,

n_{22} = number of turning points which actually did not occur and were not estimated.

Table 5.11. Contingency table (Ladd (18), Theil (30, p. 29))

	T.P.(turning points) actually occurring	T.P. did not occur	Row total
T.P. were estimated	n_{11}	n_{12}	$n_{1.}$
T.P. were not estimated	n_{21}	n_{22}	$n_{2.}$
Column total	$n_{.1}$	$n_{.2}$	n

$$n_{i.} = n_{i1} + n_{i2} \quad \text{for} \quad i = 1,2;$$

$$n_{.j} = n_{1j} + n_{2j} \quad \text{for} \quad j = 1,2;$$

$$n \;= n_{1.} + n_{2.} = n_{.1} + n_{.2}$$

Then τ and χ_1^2 are obtained from

$$\tau = \frac{n_{11}n_{22} - n_{12}n_{21}}{(n_{1.}n_{2.}n_{.1}n_{.2})^{1/2}} \tag{5.7}$$

$$\chi^2_1 = n.\tau^2 \quad \text{(Ladd (18))} \tag{5.8}$$

Kendall's tau, τ, is a rank correlation coefficient between the estimated and actual turning points. The value of τ varies from -1.0, through 0, to +1.0. When τ is -1.0, this indicates that there is a perfect negative correlation or complete disagreement in the two artificial rankings (estimated and actual turning points). When τ is 0, this indicates that there is an independence in the two artificial rankings. When τ is +1.0, this indicates that there is a complete agreement in the two artificial rankings.

The use of χ^2 with one degree of freedom is to test the hypothesis that the distribution of estimated turning points is independent of the distribution of actual turning points. If the value of χ^2 is significant, then the above hypothesis is rejected. When the value of τ is positive, it means that the model which was tested has some value in estimating the actual turning points. Conversely, if the value of τ is negative, it means that the model which was tested has no value in estimating the actual turning points.

On the other hand, if the value of χ^2 is nonsignificant, then the hypothesis will not be rejected. This can be interpreted that the distribution of estimated turning points is independent of the distribution of actual turning points. In this case, no matter what the sign of τ will be, the result suggests that the model which was tested is not precise enough in estimating the actual turning points.

The actual and estimated planted acreages from the O.L.S. and/or G.L.S. estimation of Model I, and either Model II or Model III of each crop and the graphical presentations are presented in Appendix C.

If values of a time series are represented by Y_t, a turning point is defined at time t whenever the sign of $(Y_{t+1}-Y_t)$ differs from the sign of (Y_t-Y_{t-1}).

The details of the distribution of turning points for Model I and II of corn supply response are presented in the contingency table in Table 5.12. The distribution of turning points for contingency tables of all six crops are presented in Table 5.13.

The prediction ability of Model I of corn is tested in the following χ^2 calcuation.

Table 5.12. Turning point analyses: Corn supply responses

	T.P. actually occurred		T.P. did not occur		Row Total	
	Model I	Model II	Model I	Model II	Model I	Model II
T.P. were estimated	7	8	4	3	11	11
T.P. were not estimated	4	3	6	7	10	10
Column total	11	11	10	10	21	21

Table 5.13. Turning point countings of the six crops

Crop	Model I				Model II or III[a]				n
	n_{11}[b]	n_{12}	n_{21}	n_{22}	n_{11}	n_{12}	n_{21}	n_{22}	
Corn	7	4	4	6	8	3	3	7	21
Soybeans	0	4	3	13	3	4	0	13	20
Sorghum	10	3	5	3	11	2	4	4	21
Oats	1	5	4	11	2	3	3	13	21
Barley	5	5	10	1	13	1	2	5	21
Wheat	3	6	11	1	11	1	3	6	21

[a]Model III for oats, Model II for others.

[b]Definitions of each n_{ij} are in Table 5.11.

$$\chi_1^2 = n\tau^2$$

$$= 21[\frac{42-16}{(11x10x11x10)^{1/2}}]^2$$

$$= 21(0.24)^2 = 1.21 \qquad (5.9)$$

This χ^2 is nonsignificant; i.e., we fail to reject the hypothesis. We can conclude that Model I of corn does not estimate turning points very well.

In the case of Model II of corn, the value of χ^2 is calculated.

$$\chi^2 = 23[\frac{56-9}{(11x10x11x10)^{1/2}}]^2$$

$$= 21(0.43)^2 = 3.88^{**} \qquad (5.10)$$

This χ^2 is significant at a 5 percent level; i.e., we reject the null hypothesis. Thus, it can be concluded that Model II of corn estimates turning points more precisely than does Model I.

The results of χ^2 calculation and interpretation of the turning point analyses of corn and the other crops are summarized in Table 5.14. In the interpretation column, symbol "A" shows that the χ^2 test leads to acceptance of the null hypothesis that the distribution of estimated

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** Significant at .05 level.

turning points is independent of the distribution of actual turning points; symbol "R" shows that the χ^2 test leads to rejection of the null hypothesis.

Table 5.15 summarizes the results of comparisons among the models, which were tested by the F-tests of significance for regression analyses and by the turning point analyses. Results of the F-tests show that the revised models are superior to the basic models in four out of six crops (soybeans, oats, barley, and wheat); whereas, the revised models are not superior to the basic models for two crops (corn and sorghum).

The results of turning point analyses indicate that, in general, the revised models with subjective data are superior to the basic models. In five out of six crops studied (corn, soybeans, sorghum, barley, and wheat), the revised models simulate the actual turning points very well. For only one of six crops (oats), do the results show that neither the basic nor the revised models accurately predict the actual turning points.

It is noticed that in the cases of corn and sorghum, the F-ratio tests indicate that the models with subjective variables are not superior to the basic models. However, in turning point analyses, Model II of corn and sorghum predict the actual turning points fairly well. In contrast,

Table 5.14. χ_1^2 and interpretation of turning point analyses

Crop	Model	τ	χ_1^2	Interpretation
Corn	Model I	0.24	1.21	A[a]
	Model II	0.43	3.88**	R
Soybeans	Model I	-0.21	0.88	A
	Model II	0.57	6.56**	R
Sorghum	Model I	0.16	0.54	A
	Model II	0.37	2.87*	R
Oats	Model I	-0.11	0.25	A
	Model III	0.21	0.94	A
Barley	Model I	-0.45	4.27**	R
	Model II	0.67	9.43***	R
Wheat	Model I	-0.61	7.84***	R
	Model II	0.61	7.84***	R

[a] A means accept the null hypothesis, R means reject the null hypothesis, .10 level used.

*Significant at .10 level.

**Significant at .05 level.

***Significant at .01 level.

Table 5.15. The superior model from statistical tests

Crop	Superior Model: Regression analyses (F-tests)	Superior Model: Turning point analyses (Chi Square tests)
Corn	Model I	Model II
Soybeans	Model II	Model II
Sorghum	Model I	Model II
Oats	Model III	Neither I nor III sign
Barley	Model II	Model II
Wheat	Model II	Model II

Model I (the basic models) of those two crops do not accurately predict actual turning points.

The results of turning point analyses and the F-tests of significance for regression analyses indicate that each of the revised models for soybeans, barley, and wheat is superior to the corresponding basic model. For oat supply responses, results of the F-tests indicate that Model III is superior to Model I. In contrast, the turning point analyses indicate that neither Model I nor Model III accurately predict the actual turning points.

VI. SUMMARY AND CONCLUDING REMARKS

A. Summary and Conclusions

The existing commodity-supply response studies, which were derived from traditional production theory, contained only objective variables or expected prices as market variables or policy variables. Study on the relation of actual planted acreage to intended planted acreage was nonexistent. This study focused upon the use of the March intended acreages of six U.S. major crops in estimating the farm-supply response. The main objective of the study was to determine efficient methods for using data on farmers' intentions in estimating the farm supply response. The second objective was to compare the accuracy of estimates from the basic models not containing subjective variables with the accuracy of estimates from revised models containing subjective variables.

With the assumption of maximization of the expected profit of a farm firm, the decision on how many acres of land will be planted to a certain commodity is determined by the solution of a constrained maximization problem. The traditional supply response function was derived from such an analysis. However, as a matter of fact, after the decision has been made, the actual planted acreage may deviate from the intended acreage. In this study, the major concern is to analyze this part of the farm firm's behavior, by a process called realization function approach. The realization function was developed in this study and a revised supply response model was formulated. The revised model contained March intended acreage data and other objective variables as explanatory variables.

Two other models which were the reduced form of the revised model were also constructed in order to test the superiority of the models contained in this study.

Four empirical models have been constructed and were designated as follows: Model I was the basic model which contains expected prices, expected yields and some policy variables as explanatory variables; Model II was the revised model which contains the intended acreage of the crop and competitive crops in addition to all variables contained in Model I; Model III was the model which drops the intended acreage of competitive crops from Model II; Model IV was the model containing only the intended acreage of one crop as an explanatory variable. The dependent or endogenous variables in all models were the planted acreages of the crop concerned.

Four supply response models of six U.S. major crops, i.e., corn, soybeans, sorghum, oats, barley and wheat, have been estimated by Ordinary Least Squares in the primary study. Then, the models which have significant DW statistics were reestimated by first, second and third-order autocorrelation regression procedures, with the Ordinary Least Squares, second-order and third-order autocorrelation regression selected and presented in the study. Every model of each crop uses the same procedure for providing the grounds for comparing the models. Comparisons between pairs of models were tested by the F-test of significance of a group of coefficients for regression analysis. After completion of the testing, a set of six equations, one for each crop, was selected and reestimated by the seemingly unrelated regression procedure.

To evaluate the validity of the models constructed, turning points were estimated from two models of each crop, i.e., Model I representing the basic model and Model II or Model III representing the revised model, and turning points of actual value were observed. Finally, tests of independence between estimated turning points and actual turning points were presented, analyzed and discussed.

The data used in this study were time-series and secondary data from 1952-1974, mostly from USDA publications. The results from the six U.S. major crop supply responses estimated are presented in Tables 5.1 through 5.6. Model I, or the basic model without subjective data, yields a good fit for most of the six crops. Adding subjective variables to Model I, as in Model II, tended to reduce the level of significance of other variables in equations for four of the six crops: corn, soybeans, sorghum and oats. For the barley supply response, when subjective variables were added, there was no effect on the level of significance of the other variables. For the wheat supply response, the result of adding subjective variables was to increase the level of significance of the other variables. Generally speaking, the coefficients of subjective variables in Model II of most of the farm crops studied were highly significant. It could be concluded that subjective variables provided important information in building a farm crop supply response model.

To compare the models presented, five pairs of comparisons were made. From the F-ratio calculations (when tested), Model I of corn, Model II of soybeans, Model I of sorghum, Model III of oats, Model II of barley and Model II of wheat, were considered the superior models for each crop concerned.

In general, the intended acreages of each crop considered showed very important in explaining the acreage supply response. When comparing Model III, vs. Model I, the F-ratios were significant at a 1 percent level for soybeans, oats, barley and wheat. They showed nonsignificant for corn and sorghum.

In testing the addition of all subjective variables (intended acreages of the crop itself and competitive crops) to the basic model, the results were highly significant at a 1 percent level for soybeans, oats, barley and wheat; and were nonsignificant for corn and sorghum.

Testing the addition of intended acreage of competitive crops to Model III, which contains only the intended acreage of the crop and objective variables, yielded results that were highly significant for soybeans, barley and wheat, and were nonsignificant for other crops.

After comparison of the models presented, a set of six equations composed of Model I of corn, Model II of soybeans, Model I of sorghum, Model III of oats, Model II of barley and Model II of wheat, was selected and estimated by seemingly unrelated regression. The results showed that there were improvement in the level of significance of coefficients for corn and soybean equations, no improvement for the oat and wheat equations and no explicit conclusion for the sorghum and barley equations. Tables 5.8 and 5.9 present the SUR estimates and the residual correlation matrix, respectively.

In evaluating the validity of the crop supply response models constructed, the estimated planted acreages from the regression of Model I of all six crops, Model III for oats and Model II for the other five crops were calculated. The estimated planted acreages, the actual planted acreages and differences for the six crops are presented in Tables C1 through C6. The graphical representations of those values are shown in Figures C1 through C6.

The results of turning point analyses showed that, in general, the revised model with subjective data was superior to the basic model. The revised model seems to simulate the actual turning points very well. This was especially noticeable in the cases of corn and sorghum, for which the comparison earlier indicated that adding subjective data did not result in improvement. In this analysis, the results showed that Model II of corn and Model II of sorghum estimated the actual turning points fairly well. The Chi Square test showed that there was a relationship between estimated and actual turning points. In contrast, Model I of those two crops did not estimated actual turning points very well.

For the soybean, barley, and wheat supply responses, the results of turning point analyses were consistent with the comparisons among the models by the F-tests. This indicated that the revised models of these three crops were superior to the corresponding basic models. The χ^2 test revealed that the revised models of the three crops accurately predicted the actual turning points; conversely, Kendall's τ correlation coefficient indicated that there was disagreement between the estimated and actual turning points for the basic models. The χ^2 tests and turning point analyses for oat supply response models showed that neither Model I nor Model III did accurately predict the actual turning points.

Results of the turning point analyses suggested that incorporating subjective data with objective data in estimating farm crop supply response yielded better results than using objective data alone. The realization function approach and subjective data should be taken into account in building a model of farm crop supply response.

Because there were many explanatory variables in some crop supply response equations, two methods of transformed data were introduced to conserve the degrees of freedom. The first method was to multiply expected prices and expected yields of corresponding crops included in the equation. The second method was to introduce ratios of expected prices and ratios of expected yields. The results of the regression with the transformed data were not better than the results of the regression of ordinary data. Indeed, some of them are inferior.

B. Suggestions for Further Research

In 1971, the USDA started conducting a January farmers' intention survey, and the January intention survey has been conducted every year since. It is suggested that January intention data be utilized in estimating farm supply response. Then, the results of the supply response using January intention data and the one using March intention data should be compared. In addition, it is suggested that the farm supply response model with subjective data be refined to serve as a short-run forecasting model. The evaluation of an *ex ante* forecase should be investigated in a further study.

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IX. APPENDIX A: ESTIMATED YIELD EXPECTATION EQUATIONS AND ESTIMATED VALUES OF YIELD EXPECTATIONS

Several equations of yield expectations of seven U.S. farm crops were formulated and estimated by O.L.S. The best fitting equation for each crop (which was determined by highest R^2) was selected and used to predict yield expectations. The results of yield expectation regressions are presented below. The estimated value of yield expectations are in Table A1.

Corn:

$$
\begin{aligned}
YECN_t = {} & \underset{(1.443)}{5.8830} + \underset{(2.756)}{0.6205}\, YCN_{t-1} + \underset{(0.006)}{0.0010}\, YCN_{t-2} \\
& + \underset{(0.836)}{0.1920}\, YCN_{t-3} + \underset{(3.283)}{0.6648}\, YCN_{t-4} \\
& - \underset{(-1.766)}{0.5439}\, YCN_{t-5}
\end{aligned}
$$

$$R^2 = 0.927, \quad F = 48.775$$

Soybeans:

$$
\begin{aligned}
YESB_t = {} & \underset{(2.435)}{12.0854} + \underset{(0.429)}{0.0859}\, YSB_{t-1} + \underset{(1.311)}{0.2616}\, YSB_{t-2} \\
& + \underset{(2.454)}{0.3994}\, t - \underset{(-1.394)}{0.0072}\, t^2
\end{aligned}
$$

$$R^2 = 0.7591, \quad F = 17.335$$

Sorghum:

$$\underset{}{YEGM_t} = \underset{(1.274)}{3.2477} + \underset{(4.824)}{1.1156}\ YGM_{t-1} - \underset{(-1.523)}{0.5376}\ YGM_{t-2}$$

$$+ \underset{(1.797)}{0.7342}\ YGM_{t-3} - \underset{(-0.662)}{0.3010}\ YGM_{t-4}$$

$$- \underset{(-0.286)}{0.0850}\ YGM_{t-5}$$

$$R^2 = 0.9198, \quad F = 48.150$$

Oats:

$$YEOT_t = \underset{(1.651)}{6.8926} + \underset{(1.533)}{0.3062}\ YOT_{t-1} + \underset{(1.943)}{0.4061}\ YOT_{t-2}$$

$$+ \underset{(2.479)}{0.4841}\ YOT_{t-3} + \underset{(0.052)}{0.0104}\ YOT_{t-4}$$

$$- \underset{(-1.816)}{0.3568}\ YOT_{t-5}$$

$$R^2 = 0.8075, \quad F = 17.619$$

Barley:

$$YEBY_t = \underset{(1.265)}{3.6374} + \underset{(2.817)}{0.5870}\ YBY_{t-1} + \underset{(0.384)}{0.0956}\ YBY_{t-2}$$

$$+ \underset{(0.632)}{0.1804}\ YBY_{t-3} + \underset{(0.977)}{0.2699}\ YBY_{t-4}$$

$$- \underset{(-0.830)}{0.2089}\ YBY_{t-5}$$

$$R^2 = 0.8641, \quad F = 26.698$$

Wheat:

$$YEWT_t = \underset{(12.123)}{14.4345} + \underset{(5.394)}{1.0570}\ t - \underset{(-2.351)}{0.0160}\ t^2$$

$$R^2 = 0.8777, \quad F = 86.142$$

Cotton:

$$YECT_t = \underset{(11.232)}{231.8957} + \underset{(8.382)}{28.4847}\ t - \underset{(-6.570)}{0.7739}\ t^2$$

$$R^2 = 0.8241, \quad F = 56.207$$

Table A1. Estimated yield expectation of U.S. major crops

Years	YEBY	YECN	YEGM	YEOT	YESB	YEWT	YECT
1952	28.3775	49.1808	22.0616	37.0614	20.6820	17.4617	310.384
1953	28.3572	41.1970	20.2346	35.7221	20.7866	18.4069	333.451
1954	30.2104	42.8807	19.9432	36.0611	20.8799	19.3202	354.971
1955	29.7081	42.1493	20.5902	33.9011	20.7002	20.2015	374.942
1956	29.5692	47.5145	20.1834	35.0024	21.4849	21.0508	393.365
1957	30.4978	47.2220	25.6804	38.4350	21.9478	21.8683	410.241
1958	30.6802	48.0193	29.6303	40.4548	22.7890	22.6538	425.569
1959	32.3041	54.2845	35.9647	40.6825	23.5028	23.4073	439.349
1960	30.8156	56.8236	37.3492	41.7289	23.9515	24.1289	451.581
1961	32.2907	56.3417	43.4699	45.3424	24.0012	24.8186	462.265
1962	32.1628	63.6808	44.0433	42.7574	24.3568	25.4763	471.401
1963	33.5925	63.1749	44.2707	42.5006	24.9019	26.1021	478.989
1964	35.5053	67.5414	45.5876	45.4260	24.8729	26.6960	485.030
1965	37.1533	69.1320	42.0162	44.0121	24.9625	27.2579	489.522
1966	41.7841	74.0317	53.6358	47.0430	24.8503	27.7879	492.467
1967	39.1408	73.3393	51.4101	47.1958	25.5181	28.2860	493.864
1968	41.6503	74.7674	51.0754	48.8060	25.8075	28.7521	493.713
1969	43.8554	84.3751	56.7235	50.2334	25.8779	29.1862	492.014
1970	42.7474	82.9330	51.3673	51.5616	26.6159	29.5884	488.767
1971	43.8681	79.6448	48.9860	54.2501	26.8267	29.9587	483.973
1972	45.9824	86.3952	55.8089	52.9502	26.7856	30.2971	477.630
1973	44.2379	93.9854	58.0589	50.4833	27.0795	30.6035	469.740
1974	41.9224	80.8922	55.8472	50.6075	27.1938	30.8780	460.301

X. APPENDIX B: SIMPLE CORRELATION MATRIX OF VARIABLES

Table B1. Simple correlation matrix for crop supply response model

	$APCN_t$	$APSB_t$	$APGM_t$	$APOT_t$	$APBY_t$	$APWT_t$	$AICN_t$
$APCN_t$	1.00000						
$APSB_t$	-0.53070	1.00000					
$APGM_t$	0.27352	-0.09544	1.00000				
$APOT_t$	0.65036	-0.91253	0.28889	1.00000			
$APBY_t$	0.28654	-0.56484	0.55810	0.47827	1.00000		
$APWT_t$	0.66821	-0.19309	-0.19075	0.33708	-0.36916	1.00000	
$AICN_t$	0.86437	-0.62856	0.09567	0.67471	0.46279	0.53086	1.00000
$AISB_t$	-0.51760	0.99560	-0.07069	-0.91339	-0.56488	-0.19133	-0.62877
$AIGM_t$	0.20693	-0.10698	0.87214	0.28521	0.61051	-0.19919	0.18172
$AIOT_t$	0.66451	-0.91708	0.31069	0.99510	0.60360	0.32540	0.69178
$AIBY_t$	0.25163	-0.56935	0.48631	0.52781	0.98375	-0.41538	0.44689
$AIWT_t$	0.69134	-0.20751	-0.21410	0.34260	-0.35076	0.97960	0.57128
$APSB_{t-1}$	-0.49010	0.97951	-0.09663	-0.90587	-0.57416	-0.17550	-0.60215
$PICN_t$	0.65334	0.03763	-0.01920	0.15685	-0.19555	0.79470	0.55923
$DPCN_t$	-0.84137	0.61711	-0.31065	-0.68745	-0.39732	-0.51710	-0.77749
$PSSB_t$	-0.30336	0.18490	-0.59230	-0.21771	-0.74196	0.37775	-0.33841
PSB_{t-1}	0.09213	0.63236	-0.09345	-0.43940	-0.52447	0.46245	-0.03090
$PIGM_t$	0.59864	0.04317	0.06765	0.17626	-0.14674	0.76055	0.49951
$DPGM_t$	-0.88935	0.58381	-0.39644	-0.70321	-0.44686	-0.55265	-0.81489
$PIOT_t$	0.21009	0.30544	-0.16467	-0.16095	-0.40171	0.52657	0.16232
$PIBY_t$	0.51371	0.12071	0.02155	0.09643	-0.19563	0.73601	0.46705
$PFWT_t$	0.34438	-0.00823	-0.31988	0.10970	-0.65249	0.78500	0.14286
PWT_{t-1}	0.44270	-0.02416	0.08181	0.13626	0.03479	0.45596	0.45784
$DPWT_t$	-0.05646	-0.21971	0.50803	0.32342	0.42152	-0.18524	-0.08736
$PFCT_t$	0.60761	-0.20644	-0.07067	0.35882	0.07314	0.58667	0.62736
$YECN_t$	-0.61248	0.96057	-0.24421	-0.94117	-0.60738	-0.27581	-0.70108
$YESB_t$	-0.62392	0.93915	-0.17924	-0.97232	-0.48089	-0.37643	-0.65792
$YEGM_t$	-0.69229	0.91276	-0.28149	-0.97304	-0.49791	-0.42024	-0.67866
$YEOT_t$	-0.61830	0.91780	-0.22375	-0.93311	-0.54102	-0.30158	-0.64637
$YEBY_t$	-0.57462	0.94592	-0.11741	-0.88404	-0.60369	-0.24867	-0.70864
$YEWT_t$	-0.66515	0.95046	-0.10200	-0.96201	-0.45849	-0.42754	-0.70705
$YECT_t$	-0.78312	0.74529	-0.06471	-0.87516	-0.21205	-0.71404	-0.73204
DVSIX	-0.39187	0.87435	-0.08088	-0.75953	-0.62903	-0.06290	-0.57208
DVEIGH	-0.30542	0.82037	-0.04391	-0.63425	-0.52728	0.02201	-0.47281
T52	-0.59205	0.98095	-0.11079	-0.94925	-0.52644	-0.30450	-0.66560
T67	-0.30508	-0.13972	-0.07253	-0.13427	0.22930	-0.48692	-0.11953
$T67^2$	-0.39783	0.00969	-0.17105	-0.29351	-0.01008	-0.44966	-0.26768

$AISB_t$	$AIGM_t$	$AIOT_t$	$AIBY_t$	$AIWT_t$	$APSB_{t-1}$	$PICN_t$	$DPCN_t$
1.00000							
-0.09256	1.00000						
-0.91708	0.31873	1.00000					
-0.56713	0.55032	0.56155	1.00000				
-0.21019	-0.23275	0.32949	-0.39326	1.00000			
0.98950	-0.10919	-0.91350	-0.57193	-0.18259	1.00000		
0.04194	-0.05543	0.16340	-0.22160	0.83260	0.07549	1.00000	
0.59615	-0.27306	-0.70463	-0.39822	-0.53110	0.56952	-0.52988	1.00000
0.17190	-0.62877	-0.26350	-0.76377	0.35993	0.15884	0.01568	0.31568
0.63190	-0.14244	-0.43827	-0.54103	0.49021	0.64245	0.76180	-0.01890
0.04671	0.08040	0.18986	-0.18531	0.79441	0.07173	0.96226	-0.50462
0.57566	-0.37925	-0.73092	-0.42873	-0.57884	0.55960	-0.62629	0.93831
0.32028	-0.12963	-0.16798	-0.40055	0.58532	0.38195	0.79064	-0.26662
0.12044	0.05985	0.09054	-0.24613	0.78075	0.15466	0.91917	-0.43269
-0.00278	-0.40821	0.06839	-0.71767	0.79944	0.03137	0.49673	-0.14526
-0.00293	0.11022	0.14922	0.05415	0.52031	0.05493	0.79867	-0.57288
-0.21954	0.67616	0.35701	0.40159	-0.22743	-0.24218	-0.20575	-0.16919
-0.19245	0.02342	0.36731	0.05070	0.63111	-0.12992	0.77648	-0.52444
0.95634	-0.24291	-0.94407	-0.58781	-0.29308	0.93979	-0.10702	0.72192
0.94425	-0.16444	-0.96875	-0.44791	-0.39196	0.93941	-0.14580	0.67604
0.91016	-0.27329	-0.97609	-0.46046	-0.41187	0.90612	-0.20755	0.73679
0.92493	-0.18162	-0.93723	-0.53165	-0.32089	0.92008	-0.16683	0.73931
0.94739	-0.15031	-0.89680	-0.61890	-0.27061	0.93712	-0.12679	0.74285
0.95606	-0.10002	-0.96041	-0.43468	-0.44610	0.94705	-0.18995	0.70296
0.75169	-0.04267	-0.86712	-0.15738	-0.73344	0.73833	-0.51155	0.69848
0.88018	-0.13037	-0.78305	-0.67217	-0.07372	0.87932	-0.01493	0.58911
0.82778	-0.06329	-0.66294	-0.57985	-0.00707	0.84070	0.14036	0.50216
0.98600	-0.11615	0.95005	-0.51485	-0.32191	0.97898	-0.06513	0.67234
-0.15613	-0.06270	-0.09330	0.32447	-0.46522	-0.19975	-0.43539	0.09835
0.00180	-0.18923	-0.26381	0.08623	-0.43271	-0.03415	-0.45053	0.19824

Table B1 (Continued)

	$PSSB_t$	PSB_{t-1}	$PIGM_t$	$DPGM_t$	$PIOT_t$	$PIBY_t$	$PFWT_t$
$APCN_t$							
$APSB_t$							
$APGM_t$							
$APOT_t$							
$APBY_t$							
$APWT_t$							
$AICN_t$							
$AISB_t$							
$AIGM_t$							
$AIOT_t$							
$AIBY_t$							
$AIWT_t$							
$APSB_{t-1}$							
$PICN_t$							
$DPCN_t$							
$PSSB_t$	1.00000						
PSB_{t-1}	0.22140	1.00000					
$PIGM_t$	0.00526	0.75767	1.00000				
$DPGM_t$	0.40149	-0.08948	-0.63910	1.00000			
$PIOT_t$	0.22111	0.85151	0.80618	-0.27250	1.00000		
$PIBY_t$	0.11962	0.77751	0.94668	-0.53683	0.85473	1.00000	
$PFWT_t$	0.65236	0.37622	0.45615	-0.12883	0.43256	0.48726	1.00000
PWT_{t-1}	-0.11110	0.64048	0.81233	-0.59898	0.86346	0.82671	0.14884
$DPWT_t$	-0.25719	-0.25877	-0.01140	-0.25198	-0.13942	-0.08839	-0.31082
$PFCT_t$	-0.22399	0.39398	0.77262	-0.61492	0.58332	0.66882	0.32168
$YECN_t$	0.21131	0.48692	-0.12587	0.70744	0.14765	-0.07805	-0.03201
$YESB_t$	0.08615	0.43968	-0.14995	0.67363	0.15473	-0.08192	-0.18518
$YEGM_t$	0.18920	0.39772	-0.23362	0.75525	0.12543	-0.14183	-0.16056
$YEOT_t$	0.19438	0.40229	-0.16135	0.72986	0.11708	-0.08552	-0.04926
$YEBY_t$	0.23974	0.46381	-0.13033	0.72009	0.13230	-0.06452	-0.06769
$YEWT_t$	0.08599	0.42854	-0.18762	0.70504	0.13814	-0.10981	-0.20567
$YECT_t$	-0.03541	0.07854	-0.50660	0.75590	-0.13926	-0.41936	-0.48446
DVSIX	0.36384	0.49584	-0.02776	0.59019	0.21913	0.08291	0.27217
DVEIGH	0.13214	0.53203	0.14462	0.44665	0.28728	0.20188	0.21170
T52	0.12587	0.53524	-0.06385	0.65435	0.23195	0.00698	-0.09559
T67	-0.03902	-0.31540	-0.44370	0.15899	-0.33213	-0.44321	-0.50596
$T67^2$	0.15198	-0.22120	-0.47478	0.30801	-0.25011	-0.44095	-0.34804

PWT_{t-1}	$DPWT_t$	$PFCT_t$	$YECN_t$	$YESB_t$	$YEGM_t$	$YEOT_t$	$YEBY_t$
1.00000							
0.03168	1.00000						
0.64812	-0.02166	1.00000					
-0.20049	-0.27251	-0.27897	1.00000				
-0.12604	-0.26534	-0.27317	0.95293	1.00000			
-0.17106	-0.31582	-0.34831	0.94981	0.96549	1.00000		
-0.21991	-0.29941	-0.24967	0.94559	0.96210	0.94127	1.00000	
-0.24772	-0.26841	-0.31141	0.95963	0.90660	0.90093	0.94075	1.00000
-0.14492	-0.21721	-0.34461	0.95182	0.98800	0.96471	0.94951	0.92800
-0.30586	-0.11552	-0.57639	0.78509	0.88163	0.88588	0.80868	0.74311
-0.16230	-0.24486	-0.24153	0.85530	0.77430	0.78865	0.84121	0.92628
-0.06214	-0.20041	0.08691	0.79505	0.73462	0.66675	0.79496	0.83841
-0.08017	0.24396	-0.24513	0.96836	0.98109	0.94892	0.95681	0.95219
-0.15352	0.03797	-0.56733	-0.08877	0.00445	0.09346	-0.11899	-0.18080
-0.18367	-0.08037	-0.64684	0.06852	0.14097	0.23938	0.03987	-0.00434

Table B1 (Continued)

	$YEWT_t$	$YECT_t$	DVSIX	DVEIGH	T52	T67	$T67^2$
$APCN_t$							
$APSB_t$							
$APGM_t$							
$APOT_t$							
$APBY_t$							
$APWT_t$							
$AICN_t$							
$AISB_t$							
$AIGM_t$							
$AIOT_t$							
$AIBY_t$							
$AIWT_t$							
$APSB_{t-1}$							
$PICN_t$							
$DPCN_t$							
$PSSB_t$							
PSB_{t-1}							
$PIGM_t$							
$DPGM_t$							
$PIOT_t$							
$PIBY_t$							
$PFWT_t$							
PWT_{t-1}							
$DPWT_t$							
$PFCT_t$							
$YECN_t$							
$YESB_t$							
$YEGM_t$							
$YEOT_t$							
$YEBY_t$							
$YEWT_t$	1.00000						
$YECT_t$	0.90563	1.00000					
DVSIX	0.79965	0.56937	1.00000				
DVEIGH	0.72639	0.43653	0.82496	1.00000			
T52	0.98821	0.83004	0.84611	0.79772	1.00000		
T67	0.03136	0.33980	-0.30146	-0.65425	-0.08143	1.00000	
$T67^2$	0.17250	0.44033	-0.09840	-0.52154	0.06790	0.95805	1.00000

XI. APPENDIX C: ACTUAL AND ESTIMATED VALUES OF PLANTED ACREAGES

Table C1. Actual and estimated U.S. corn acreage (in thousands) planted from Model I (model without subjective variables) and Model II (model with subjective variables, 1952-1974)

Year	Model I Model without subjective variables			Model II Model with subjective variables		
	Actual	Estimated	Deviation	Actual	Estimated	Deviation
1952	82230	82899.4	-699.4	82230	82877.2	-647.2
1953	81574	81281.4	292.6	81574	81156.1	417.9
1954	82185	80932.5	1252.5	82185	81613.1	571.9
1955	80932	81621.1	-689.1	80932	81088.8	-156.8
1956	77828	77315.6	512.4	77828	77811.4	16.6
1957	73180	74349.8	-1169.8	73180	73964.3	-784.3
1958	73351	73944.7	593.7	73351	73268.3	82.7
1959	82742	82169.7	572.3	82742	81932.3	809.7
1960	81425	80627.1	797.9	81425	81231.2	193.8
1961	65991	66634.2	-634.2	65991	67496.5	-1505.5
1962	65017	67100.4	-2083.4	65017	66118.1	-1101.1
1963	68771	68356.7	414.3	68771	67987.3	783.7
1964	65823	64636.5	1186.5	65823	64910.9	912.1
1965	65171	64350.7	820.3	65171	64764.4	406.6
1966	66347	64855.8	1491.2	66347	65748.3	598.7
1967	71156	69389.2	1766.8	71156	69342.9	1813.1
1968	65126	66948.0	-1822.0	65126	65852.2	-726.2
1969	64264	64854.3	-590.3	64264	64611.8	-347.8
1970	66849	69772.0	-2923.0	66849	70290.2	-3441.2
1971	74055	72222.3	1832.7	74055	72424.1	1630.9
1972	66972	65848.8	1123.2	66972	65890.5	1081.5
1973	71912	71786.3	125.7	71912	71346.6	565.4
1974	77746	78750.4	-1004.4	77746	78920.4	-1174.4

Table C2. Actual and estimated U.S. soybean acreage (in thousands) planted from Model I (model without subjective variables) and Model II (model with subjective variables, 1953-1974)

Year	Model I Model without subjective variables			Model II Model with subjective variables		
	Actual	Estimated	Deviation	Actual	Estimated	Deviation
1953	16394	17259.2	-865.2	16394	15795.5	598.5
1954	18541	19629.9	-1088.9	18541	19102.1	-561.1
1955	19674	18313.2	1360.8	19674	19963.3	-289.3
1956	21700	20449.7	1250.3	21700	21840.2	-140.2
1957	21938	21262.6	675.4	21938	22354.6	-416.6
1958	25108	22383.7	2724.3	25108	23405.7	1702.3
1959	23349	23474.0	-125.0	23349	23152.3	196.7
1960	24440	24658.3	-218.3	24440	25121.8	-681.8
1961	27787	26319.8	1467.2	27787	27300.6	486.4
1962	28418	30813.4	-2395.4	28418	28780.1	-362.1
1963	29462	31833.6	-2371.6	29462	29473.6	-11.6
1964	31605	34694.8	-3089.8	31605	32342.3	-737.3
1965	35227	36654.7	-1427.7	35227	34516.0	711.0
1966	37294	38977.4	-1683.4	37294	38243.8	-949.8
1967	40819	39605.2	1213.8	40819	40707.5	111.5
1968	42265	39978.7	2286.3	42265	41005.2	1259.8
1969	42534	43187.2	-653.2	42534	43225.2	-691.2
1970	43082	43280.4	-198.4	43082	42828.9	253.1
1971	43472	42342.5	1129.5	43472	45582.2	-2110.2
1972	46885	46076.2	808.8	46885	45496.0	1389.0
1973	56675	54257.9	2417.1	56675	55337.6	1337.4
1974	53580	54371.9	-791.9	53580	54781.6	-1201.6

Table C3. Actual and estimated U.S. sorghum acreage (in thousands) planted from Model I (model without subjective variables) and Model II (model with subjective variables, 1952-1974)

Year	Model I Model without subjective variables			Model II Model with subjective variables		
	Actual	Estimated	Deviation	Actual	Estimated	Deviation
1952	12289	12390.9	-101.9	12289	12704.1	-415.1
1953	14590	15106.1	-516.1	14590	14715.1	-125.1
1954	20148	19190.4	957.6	20148	19176.8	971.2
1955	23921	24049.8	-128.8	23921	24478.1	-557.1
1956	21384	22898.3	-1514.3	21384	21932.8	-548.8
1957	26886	24088.9	2797.1	26886	25415.2	1470.8
1958	20675	23021.5	-2346.5	20675	21893.0	-1218.0
1959	19508	18919.2	588.8	19508	19912.1	-404.1
1960	19598	19133.5	464.5	19598	18827.2	770.8
1961	14294	15410.8	-1116.8	14294	14469.1	-175.1
1962	15060	14061.9	998.1	15060	15202.8	-142.8
1963	17516	17146.3	369.7	17516	17575.7	-59.7
1964	16770	17366.2	-596.2	16770	15827.3	942.7
1965	17079	17004.2	74.8	17079	17905.8	-826.8
1966	16372	16726.8	-354.8	16372	16710.5	-338.5
1967	18945	18561.9	383.1	18945	18157.7	787.3
1968	17793	17924.5	-131.5	17793	18401.0	-608.0
1969	17231	17049.2	181.8	17231	16807.9	423.1
1970	16957	17541.4	-584.4	16957	17425.7	-468.7
1971	20756	19943.5	812.5	20756	20000.8	755.2
1972	17295	17770.3	-475.3	17295	17668.5	-373.5
1973	19231	18973.2	257.8	19231	19335.5	-104.5
1974	17733	17926.5	-193.5	17733	17672.7	60.3

Table C4. Actual and estimated U.S. oat acreage (in thousands) planted from Model I (model without subjective variables) and Model III (model with subjective variables, 1952-1974)

Year	Model I Model without subjective variables			Model III Model with subjective variables		
	Actual	Estimated	Deviation	Actual	Estimated	Deviation
1952	42341	43758.9	-1417.9	42341	43055.0	-714.0
1953	43220	42781.0	439.0	43220	43214.3	5.7
1954	46898	46718.6	179.4	46898	46774.4	123.6
1955	47494	46544.7	949.3	47494	46523.7	970.3
1956	44205	44794.8	-589.8	44205	44992.2	-787.2
1957	41840	40156.8	1683.2	41840	41342.4	497.6
1958	37699	38236.6	-537.6	37699	38228.7	-529.7
1959	35064	36921.6	-1857.6	35064	35036.8	27.2
1960	31419	32564.1	-1145.1	31419	32589.0	-1170.0
1961	32314	30523.7	1790.3	32314	30955.8	1358.2
1962	29500	29144.8	355.2	29500	29356.5	143.5
1963	28054	26678.4	1375.6	28054	27020.8	1033.2
1964	25634	27536.1	-1902.1	25634	27120.5	-1486.5
1965	24046	24481.4	-435.4	24046	24329.5	-283.5
1966	23343	23305.3	37.7	23343	23417.8	-74.8
1967	20719	19275.3	1443.7	20719	20058.8	660.2
1968	23342	24494.3	-1152.3	23342	22715.5	626.5
1969	23561	24020.9	-459.9	23561	23844.7	-283.8
1970	24469	24024.3	444.7	24469	24978.9	-509.9
1971	21956	21185.5	770.5	21956	22211.0	-255.0
1972	20178	20082.2	95.8	20178	19726.2	451.8
1973	19147	19387.7	-240.7	19147	19183.3	-36.3
1974	18100	18669.6	-569.6	18100	18033.7	66.3

Table C5. Actual and estimated U.S. barley acreage (in thousands) planted from Model I (model without subjective variables) and Model II (model with subjective variables, 1952-1974)

Year	Model I Model without subjective variables			Model I Model with subjective variables		
	Actual	Estimated	Deviation	Actual	Estimated	Deviation
1952	9190	10864.9	-1674.9	9190	9518.4	-328.4
1953	9615	9534.5	80.5	9615	9412.1	202.9
1954	14740	13433.0	1307.0	14740	14744.7	-4.7
1955	16293	16042.0	251.0	16293	16008.0	284.2
1956	14732	15576.1	-844.1	14732	15067.9	-335.9
1957	16398	15675.7	722.3	16398	16375.3	22.7
1958	16150	16309.5	-159.5	16150	16191.8	-41.8
1959	16766	16199.1	566.9	16766	16512.0	254.0
1960	15527	15481.1	45.9	15527	15861.3	-334.3
1961	15623	15178.1	444.9	15623	15475.0	148.0
1962	14380	13809.0	571.0	14380	14506.8	-126.8
1963	13452	13153.1	298.9	13452	13116.6	335.4
1964	11652	14257.7	-2605.7	11652	11808.1	-156.1
1965	10123	9580.9	542.1	10123	10170.3	-47.3
1966	11184	10939.2	244.8	11184	11275.1	-91.1
1967	10077	11418.2	-1341.2	10077	9944.4	132.6
1968	10486	10974.0	-488.0	10486	10479.0	7.0
1969	10291	9126.9	1164.1	10291	10266.5	24.5
1970	10490	9833.3	656.7	10490	10691.5	-201.5
1971	11115	10601.8	513.2	11115	10865.6	249.4
1972	10639	11114.1	-475.3	10639	10839.0	-200.0
1973	11229	11928.0	-699.0	11229	11023.9	205.1
1974	9117	8552.1	564.9	9117	9317.1	-200.1

Table C6. Actual and predicted U.S. wheat acreage (in thousands) planted from Model I (model without subjective variables) and Model II (model with subjective variables, 1952-1974)

Year	Model I Model without subjective variables			Model II Model with subjective variables		
	Actual	Estimated	Deviation	Actual	Estimated	Deviation
1952	21648	20893.3	754.7	21648	21446.5	201.5
1953	21844	20415.1	1428.9	21844	21954.0	-110.0
1954	15922	17553.4	-1631.4	15922	15944.2	-22.2
1955	13949	14643.8	-694.8	13949	14216.0	-267.0
1956	16237	13954.4	2282.6	16237	15522.0	715.0
1957	12423	13759.7	-1336.7	12423	12938.3	-515.3
1958	12343	13079.2	-736.2	12343	12433.1	-90.1
1959	13091	12589.7	501.3	13091	12654.7	436.3
1960	12181	12329.2	-148.2	12181	12867.3	-686.3
1961	12218	13222.7	-1004.7	12218	11722.5	495.5
1962	10379	10646.7	-267.7	10379	10343.9	35.1
1963	11075	10992.8	82.2	11075	11179.6	-104.6
1964	12040	10046.2	1993.8	12040	12142.6	-102.6
1965	12219	11773.5	445.5	12219	12210.6	8.4
1966	11359	11948.2	-589.2	11359	10887.3	471.7
1967	13615	13983.4	-368.4	13615	14230.1	-615.1
1968	13193	14053.6	-860.6	13193	12712.4	480.6
1969	11112	12049.2	-937.2	11112	11256.1	-144.1
1970	11116	11142.6	-26.6	11116	11652.7	-536.7
1971	15750	13982.9	1767.1	15750	14918.6	831.4
1972	12730	14148.9	-1418.9	12730	13209.7	-479.7
1973	15746	13771.2	1974.8	15746	15781.6	-35.6
1974	18762	19404.7	-642.7	18762	18509.9	252.1

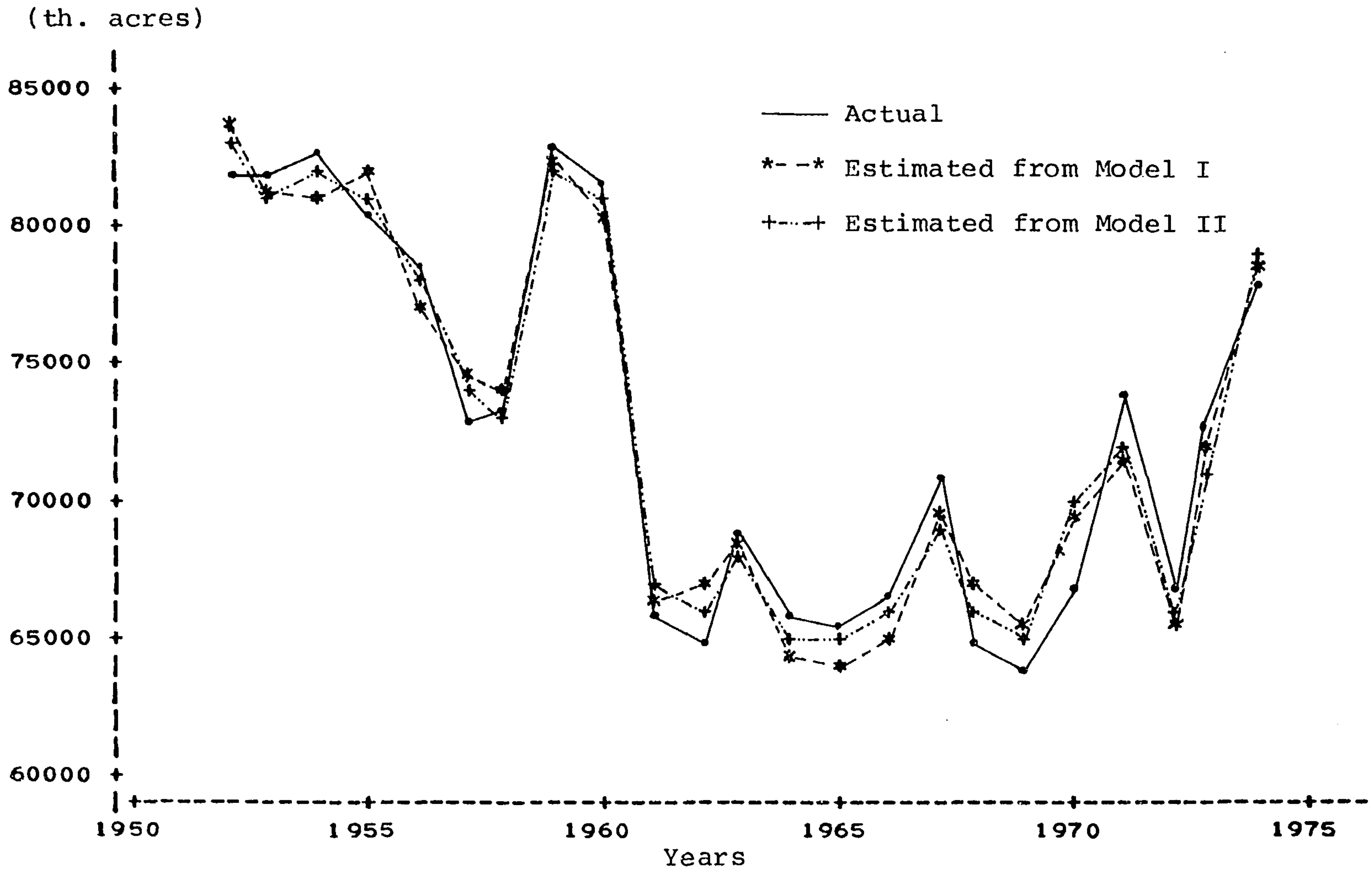

Figure C1. Actual and estimated U.S. corn acreage, 1952-1974

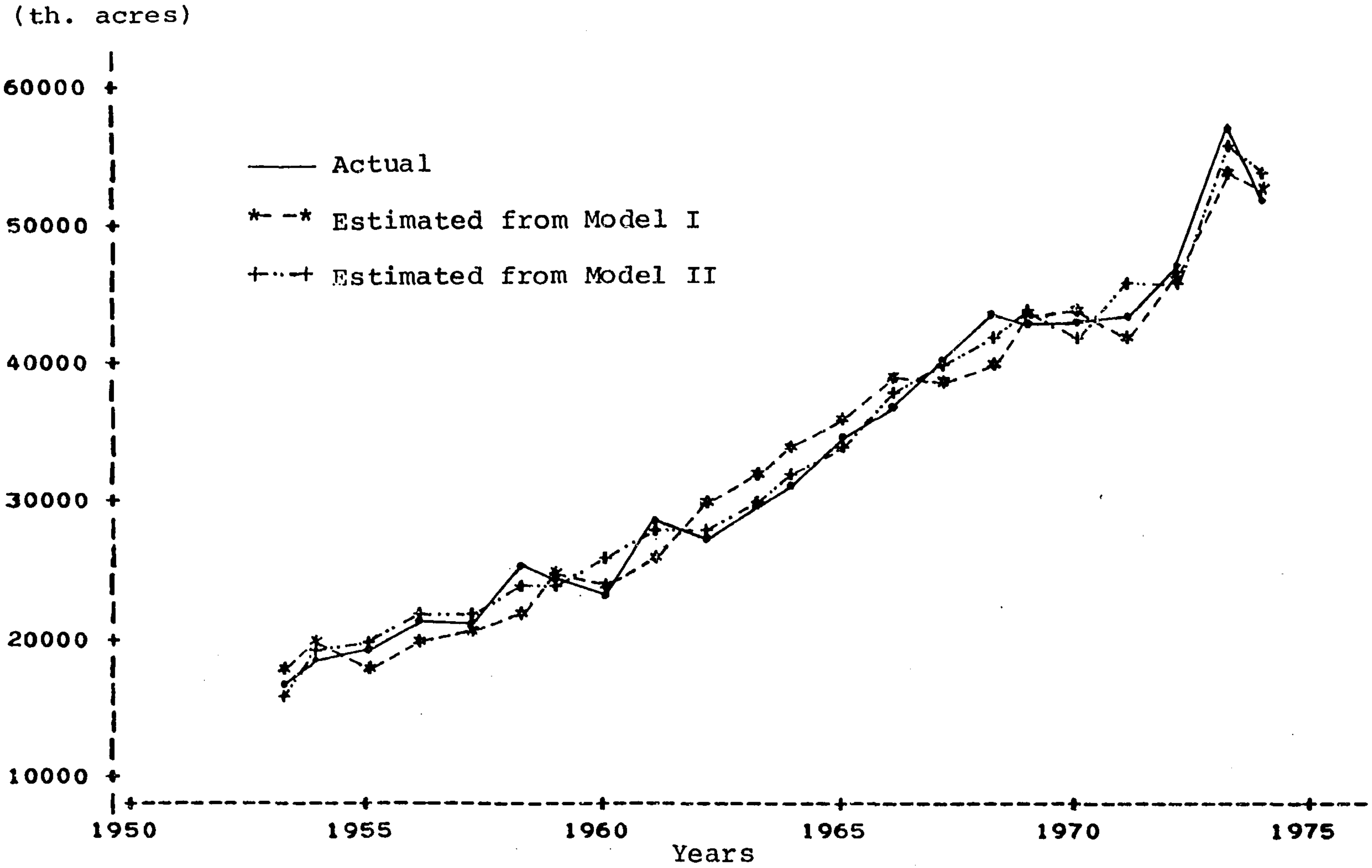

Figure C2. Actual and estimated U.S. soybean acreage, 1953-1974

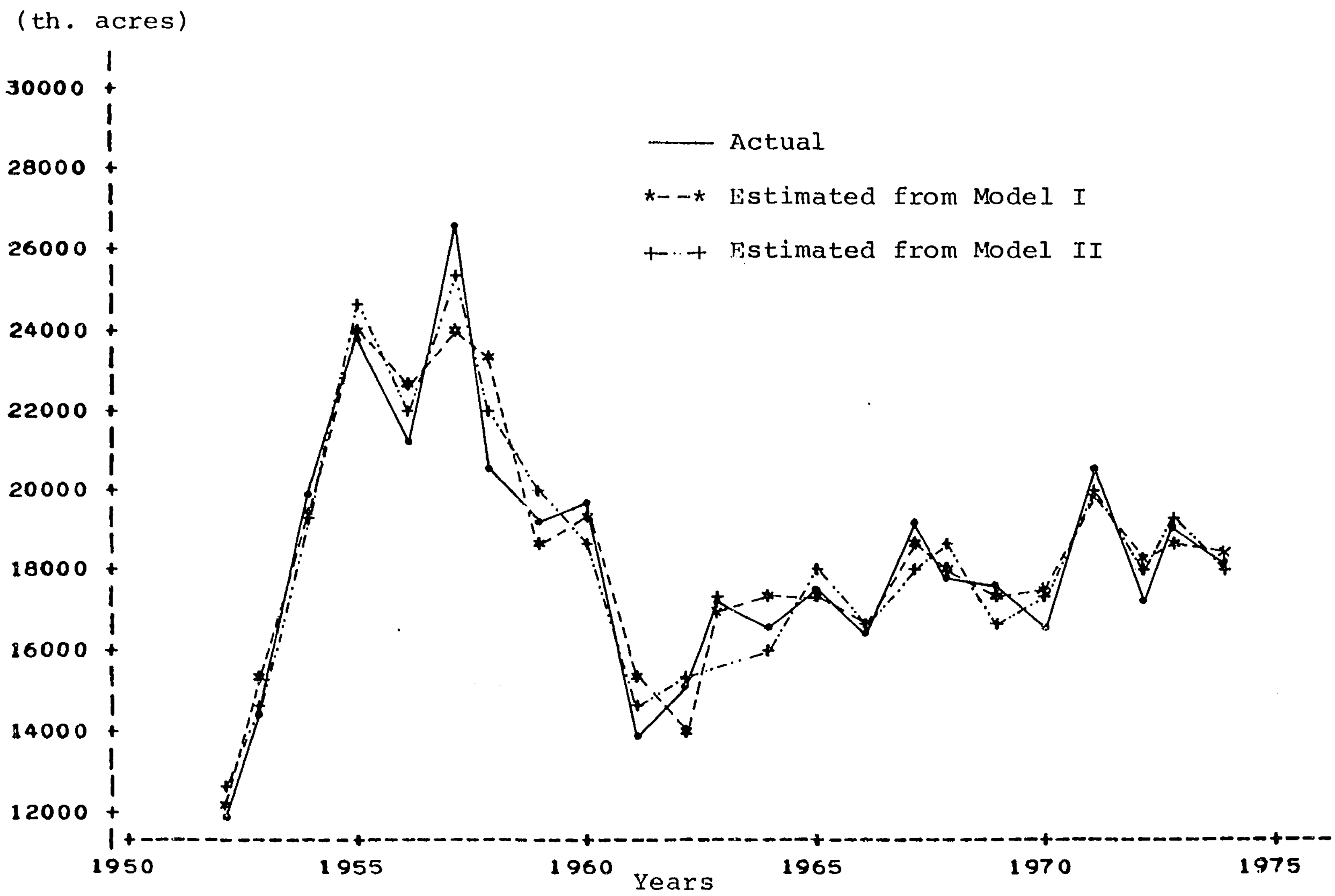

Figure C3. Actual and estimated U.S. sorghum acreage, 1952-1974

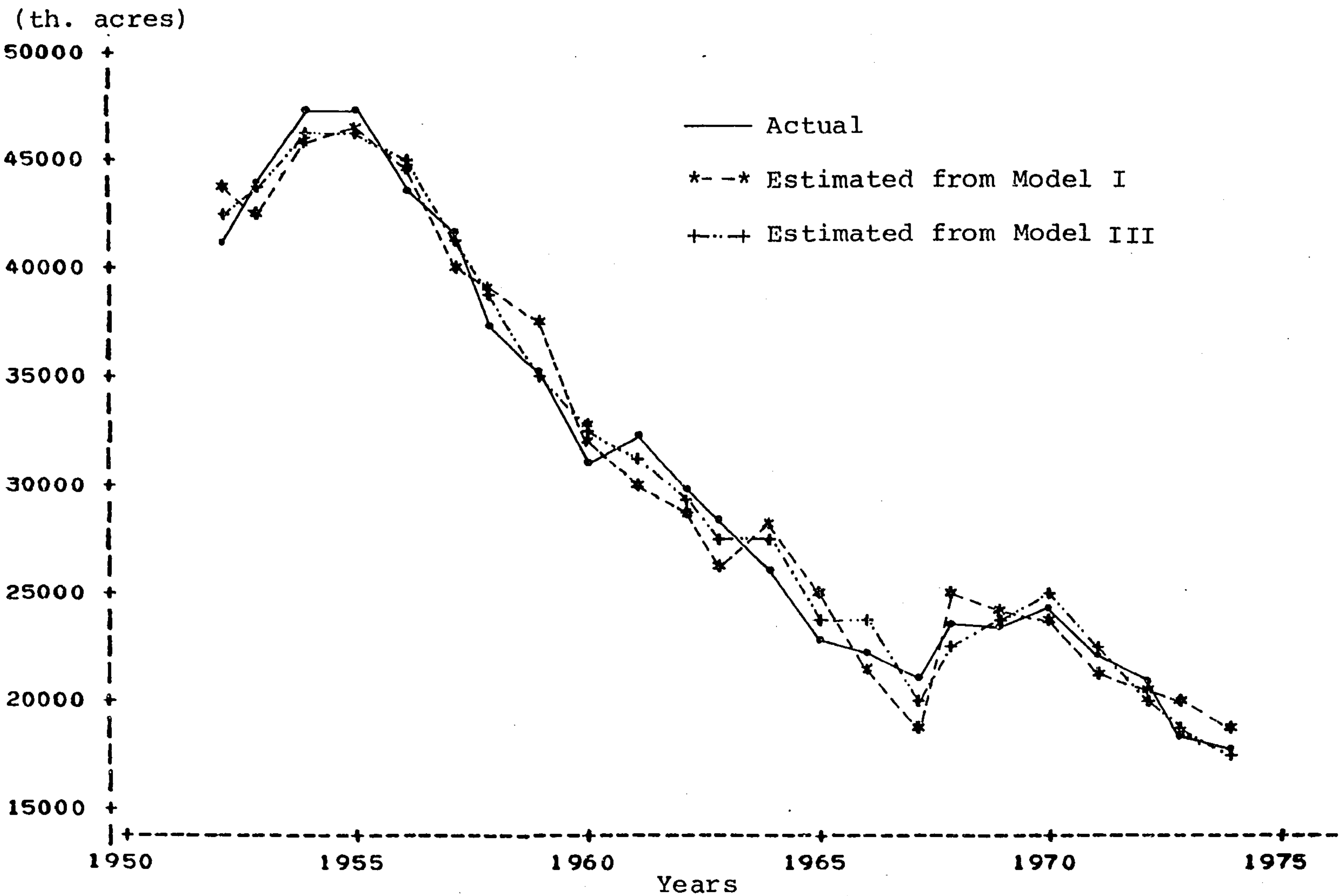

Figure C4. Actual and estimated U.S. oat acreage, 1952-1974

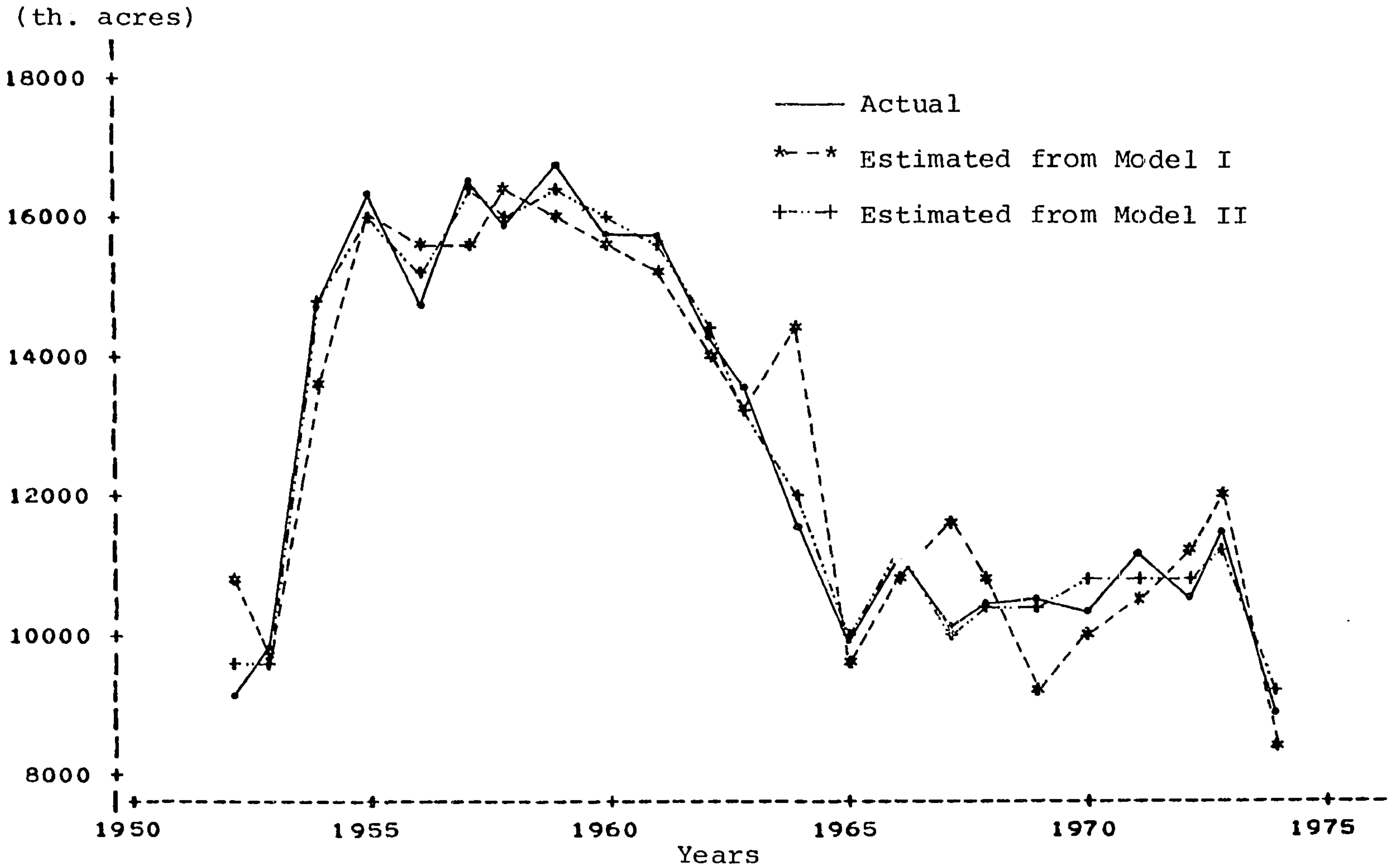

Figure C5. Actual and estimated U.S. barley acreage, 1952-1974

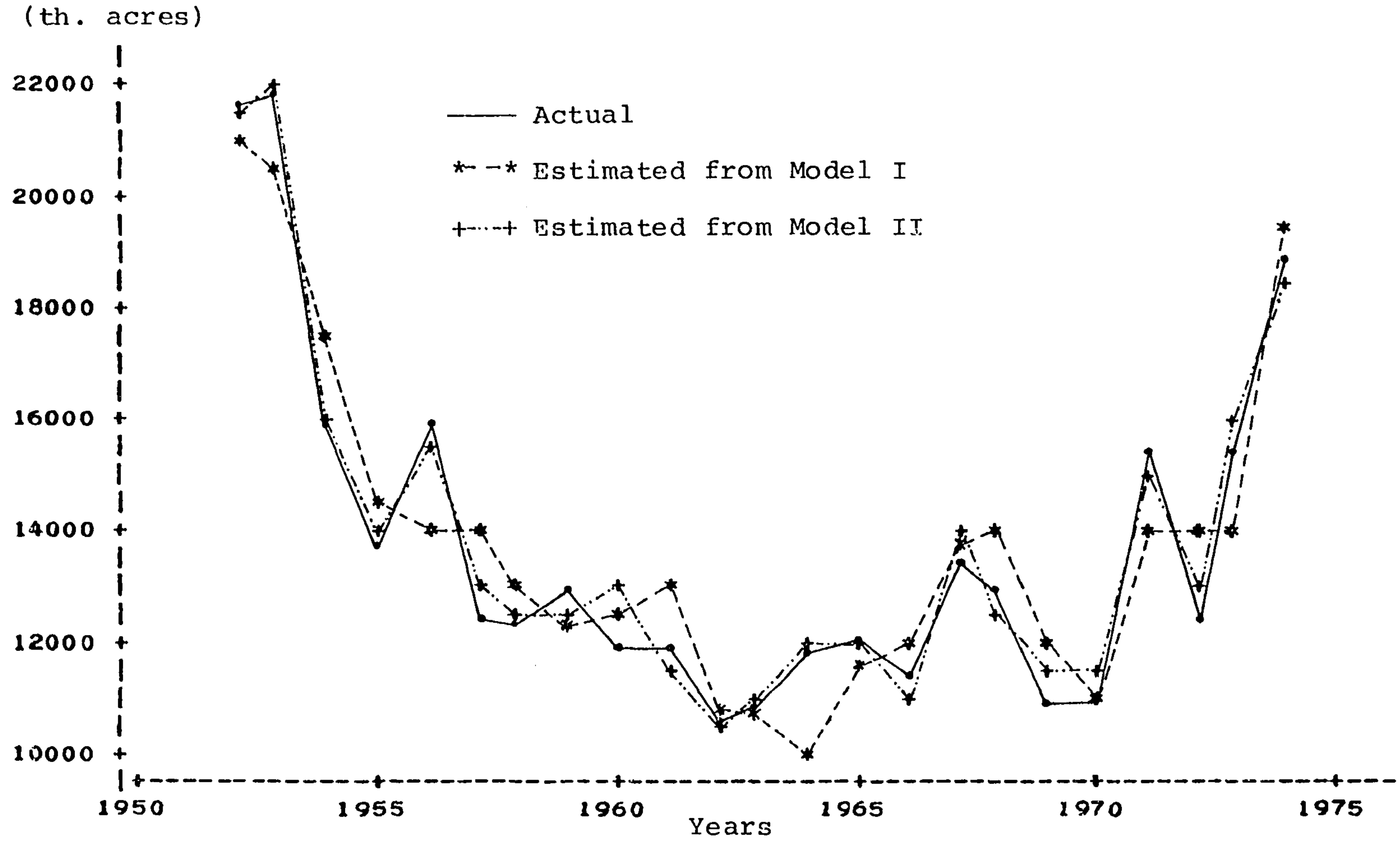

Figure C6. Actual and estimated U.S. wheat acreage, 1952-1974